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## Titre de la thèse :

## Vers une meilleure estimation des stocks de carbone dans les forêts exploitées à Diptérocarpées de Bornéo

**Présentée par Andes Hamuraby ROZAK**

**Le 29 novembre 2018**

**Sous la direction de M. Plinio SIST (Directeur de thèse)**
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UNIVERSITY OF COPENHAGEN
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# PhD Thesis

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# Towards better estimates of carbon stocks in Bornean logged-over Dipterocarp forests

Supervisors: Plinio Sist
Karsten Raulund-Rasmussen

Submitted on: 13 Sepember 2018

# Towards better estimates of carbon stocks in Bornean logged-over Dipterocarp forests

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# Table of Contents

# List of Tables

# List of Figures

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## List of acronyms

| | | |
|---|---|---|
| AFOLU | : | Agroforestry, Forestry, and Other Land Use |
| AGB | : | Above-Ground Biomass |
| $AGC_{5\text{-}20}$ | : | Above-Ground Carbon stored in AGB (tree DBH 5-20 cm) |
| $AGC_{>20}$ | : | Above-Ground Carbon stored in AGB (tree DBH >20 cm) |
| BGB | : | Below-Ground Biomass |
| $BGC_{>20}$ | : | Below-Ground Carbon stored in BGB (tree DBH >20 cm) |
| $BGC_{5\text{-}20}$ | : | Below-Ground Carbon stored in BGB (tree DBH 5-20 cm) |
| C | : | Carbon |
| CGIAR | : | The Consultative Group on International Agricultural Research |
| CIFOR | : | Center for International Forestry Research |
| CIRAD | : | Centre de cooperation International en Recherche Agronomique pour le Développement (the French agricultural research centre for international development) |
| $CO_2$ | : | Carbon dioxide |
| CVL | : | Conventional Logging |
| DBH | : | Diameter of Breast Height |
| DF | : | Default Factor |
| FAO | : | Food and Agricultural Organization |
| FAS | : | Fixed-Area Sampling method |
| FSC | : | Forest Stewardship Council |
| HLL | : | Hutansanggam Labanan Lestari, an FSC-certified forest concessionaire in Berau (East Kalimantan) |
| IPCC | : | The Intergovernmental Panel on Climate Change |
| ITTO | : | International Tropical Timber Organization |
| LIS | : | Line-Intersect Sampling method |
| MRF | : | Malinau Research Forests, formerly known as Bulungan Research Forests |
| REDD+ | : | Reducing Emissions from Deforestation and forest Degradation |
| RIL | : | Reduced-Impact Logging |
| SFM | : | Sustainable Forest Management |
| SOC | : | Soil Organic Carbon |
| STREK | : | Silvicultural Treatment for the Regeneration of logged-over forest in East Kalimantan |
| TmFO | : | Tropical managed Forest Observatory |
| TPTI | : | Tebang Pilih Tanam Indonesia (the Indonesian selective logging and planting system) |
| UNFCCC | : | United Nations Framework Convention on Climate Change |

Abstract

Tropical forests are a major reservoir of biodiversity and carbon (C), playing a pivotal role in global ecosystem function and climate regulation. However, most of the tropical forests, especially Bornean forests in Southeast Asia, are under intense pressure and threatened by anthropogenic activities such as logging, mining industry, agriculture and conversion to industrial plantation. In 2010, the area of production forests in Borneo was 26.8 million ha (approx. 36% of the total land area of Borneo) including 18 million ha (approx. 24%) of logged forests. Production forests are thus emerging as a dominant land-use, playing a crucial role in trading-off provision of goods and maintenance of ecosystem services, such as C and biodiversity retention.

Selective logging is known to reduce both above- and below-ground biomass through the removal of a few large trees, while increasing deadwood stocks through collateral damages. By creating large gaps in the canopy, microclimates in the understory and on the forest floor change locally speeding up the decomposition of litter and organic matter. The extent of incidental damages, canopy openness, as well as the speed of C recovery, was shown to be primarily related to logging intensity. However, empirical evaluations of the long-term effect of logging intensity on C balance in production forests remain rare.

The present thesis aims to assess the long-term effect of logging intensity on C sequestration in a north Bornean Dipterocarp forests (Malinau District, North Kalimantan) logged in 1999/2000. Five main C pools, namely above-ground (AGC) and below-ground (BGC) carbon in living trees, deadwood, litter, and soil organic carbon (SOC) were estimated along a logging intensity gradient (ranging from 0 to 57% of initial biomass removed).

Our result showed that total C stocks 16 years after logging, ranged from 218-554 Mg C $ha^{-1}$ with an average of 314 Mg C $ha^{-1}$. A difference of 95 Mg C $ha^{-1}$ was found between low logging intensity (<2.1% of initial biomass lost) and high logging intensity (>19%). Most C (approx. 77%) was found in living trees, followed by soil (15%), deadwood (6%), and a minor fraction in litter (1%). The imprint of logging intensity was still detectable 16 years after logging, and logging intensity thus was the main driver explaining the reduction of $AGC_{>20}$, $BGC_{>20}$, deadwood, and total C stocks and an increase in deadwood. Solely, logging intensity explained 61%, 63%, 38%, and 48% of variations of $AGC_{>20}$, $BGC_{>20}$, deadwood, and total C stocks, respectively. Logging intensity also significantly reduced SOC stocks in the upper 30 cm layer. For total SOC stocks (0-100 cm), the negative influence of logging intensity was still perceptible, being significant in conjunction with other variables.

Our results quantify the long-term effect of logging on forest C stocks, especially on AGC and deadwood. High logging intensity (50% reduction of initial biomass) reduced total C stocks by 27%. AGC recovery was lower in high logging intensity plots, suggesting lowered forest resilience to logging. Our study showed that maintaining logging intensity, below 20% of the initial biomass, limit the long-term effect of logging on AGC and deadwood stocks.

**Keywords**: Above-ground biomass; below-ground biomass; deadwood; Dipterocarp forests; litter; tropical logged forests; soil organic carbon

## Résumé (français)

Les forêts tropicales constituent le principal réservoir de biodiversité et de carbone (C), jouant un rôle central dans le cycle du carbone, le maintien de la biodiversité, la régulation du climat et l'équilibre fonctionnel général de la biosphère. Cependant, la plupart des forêts tropicales, en particulier les forêts de Bornéo en Asie du Sud-Est, subissent une pression intense et sont menacées par des activités anthropiques telles que l'exploitation forestière, l'industrie minière l'agriculture et la conversion en plantations industrielles. En 2010, la superficie des forêts de production de Bornéo était de 26,8 millions d'ha (environ 36% de la superficie totale de l'île, dont 18 millions ha (environ 24%) déjà exploités. Par conséquent, les forêts de production occupent donc une place importante à Bornéo et jouent un rôle essentiel dans la compensation des biens fournis et la maintenance des services écosystémiques, tels que la conservation du C et de la biodiversité.

L'exploitation sélective réduit la biomasse aérienne et souterraine par l'élimination de quelques grands arbres, et augmente les stocks de bois mort par des dommages collatéraux. En créant des trouées dans la canopée, le microclimat dans les sous-étages et au sol change localement et accélèrent la décomposition de la litière et de la matière organique. L'importance des dégâts, de l'ouverture de la canopée et de la rapidité du rétablissement du C s'est avéré principalement liée à l'intensité de l'exploitation forestière. Cependant, les évaluations empiriques de l'effet à long terme de l'intensité de l'exploitation forestière sur l'équilibre du C dans les forêts de production restent rares.

La présente thèse se concentre principalement sur l'évaluation de l'effet à long terme de l'intensité de l'exploitation forestière sur la séquestration de carbone dans une forêt à Diptérocarpées de Nord Bornéo (District de Malinau, Kalimantan Nord) exploitée en 1999/2000. Cinq principaux réservoirs de C, à savoir le C aérien dans les arbres vivants (AGC), le C souterrain dans les arbres vivants (BGC), le bois mort, la litière et le C organique du sol (SOC) ont été estimés le long d'un gradient d'intensité d'exploitation (0-57% de la biomasse perdue).

Nos résultats ont montré que les stocks totaux de C, 16 ans après l'exploitation, variaient de 218 à 554 Mg C ha$^{-1}$ avec une moyenne de 314 Mg C ha$^{-1}$. Une différence de 95 Mg C ha$^{-1}$ a été observée entre une faible intensité d'exploitation forestière (<2,1% de la biomasse initiale perdue) et une intensité d'exploitation élevée (>19%). La plus grande partie du C (environ 77%) était présente dans les arbres vivants, suivie par les stocks du sol (15%), les stocks de bois mort (6%) et une fraction mineure des stocks de litière (1%). L'empreinte de l'intensité de l'exploitation forestière était encore détectable 16 ans après l'exploitation et a été le principal facteur expliquant la réduction des $AGC_{>20}$, $BGC_{>20}$, du bois mort et des stocks de C et une augmentation du bois mort. L'intensité de l'exploitation expliquait à elle seule 61%, 63%, 38% et 48% des variations des $AGC_{>20}$, $BGC_{>20}$, du bois mort et des stocks de C totaux, respectivement. L'intensité de l'abattage a également réduit considérablement les stocks de SOC dans la couche supérieure de 30 cm. Pour l'ensemble des stocks de SOC (0-100 cm), l'influence de l'intensité de l'exploitation était encore perceptible, en conjonction avec d'autres variables.

Nos résultats quantifient l'effet à long terme de l'exploitation forestière sur les stocks de C forestier, en particulier sur les AGC et les bois morts. L'intensité élevée de l'exploitation forestière (réduction de 50% de la biomasse initiale) a réduit les stocks totaux de C de 27%. La récupération de l'AGC était plus faible dans les parcelles d'intensité d'exploitation forestière élevée, ce qui suggère une résilience plus faible de la forêt à l'exploitation forestière. Par conséquent, une intensité d'exploitation forestière inférieure à 20%, devrait être envisagé afin de limiter l'effet à long terme sur les AGC et le bois mort.

**Mots-clés** : biomasse aérienne ; biomasse souterraine ; bois morts ; Forêt de Diptérocarpées ; litière ; forêt tropicales exploitées ; carbone organique du sol

# Resumé (Danks)

Tropiske skove er rige på biodiversitet og er samtidigt et stort kulstoflager (C), og spiller dermed en afgørende rolle i globale økosystemfunktioner og regulering af klimaet. Imidlertid er de fleste af de tropiske skove, under stærkt pres og truet af menneskelige aktiviteter som skovhugst, minedrift og omdannelse til monokulturplantager, især på Borneo i Sydøstasien. I 2010 nåede arealet med skovhugst på Borneo 18 mio. ha (ca. 24% af Borneos samlede areal), eller 26,8 mio. ha (ca. 36%) hvis også skove officielt afsat til træproduktion men hvor hugst endnu ikke er gennemført regnes med. Produktionsskove er således blevet en dominerende arealanvendelse, der spiller en afgørende rolle i handel af varer og vedligeholdelse af økosystemtjenester, såsom kulstoflagring og biodiversitetsbeskyttelse.

Selektiv hugst er kendt for at reducere både den over- og underjordisk biomasse gennem fjernelse af nogle få store træer, samtidig med at mængden af dødt ved øges gennem følgeskader. Ved at skabe store huller i kronelaget ændres mikroklimaet i underskoven og på skovbunden lokalt og fremskynder nedbrydning af førne og organisk materiale. Omfanget af hændelige skader, kronetætheden, samt hastigheden hvorved kulstoflagre genopbygges er primært relateret til hugstintensiteten. Imidlertid er empiriske undersøgelser af den langsigtede effekt af hugstintensiteten på kulstofbalancen i produktionsskove sjældne.

Denne afhandling undersøger den langsigtede effekt af hugstintensitet på kulstofbindingen i Dipterocarp-skovene på Borneo. De fem største kulstoflagre, nemlig overjordisk (AGC) og underjordisk (BGC) kulstof i levende træer, dødt ved, førne og jordens organisk kulstof (SOC) blev estimeret langs en gradient af hugstintensitet (fra 0 til 57% biomassefjernelse) i Malinau Research Forests (MRF, i Nord Kalimantan) skovet i 1999/2000.

Vores resultat viste, at de samlede kulstoflagre varierede fra 218-554 Mg C ha$^{-1}$ med et gennemsnit på 314 Mg C ha$^{-1}$, 16 år efter skovning i MRF. En forskel på 95 Mg C ha$^{-1}$ blev fundet mellem lav hugstintensitet (<2,1% af den oprindelige biomasse fjernet) og høj hugstintensitet (>19%). Størstedelen kulstof (ca. 77%) blev fundet i levende træer, efterfulgt af SOC-lagret (15%), dødt ved (6%) og en mindre fraktion i førne (1%). Effekten af skovdrift var stadig påviselig 16 år efter, med hugst som det primære forklarende parameter, der forklarede reduktionen af $AGC_{>20}$, $BGC_{>20}$, dødt ved og totalt kulstoflager og en stigning i dødt ved. Hugstintensiteten alene forklarede 61%, 63%, 38% og 48% af variationen af henholdsvis $AGC_{>20}$, $BGC_{>20}$, dødt ved og totalt kulstoflager. Hugstintensiteten reducerede også SOC-lagrene betydeligt i det øverste 30 cm lag. For det samlede SOC-lager (0-100 cm) var indflydelsen af hugstintensitet stadig synlig, idet den var signifikant i kombination med andre variabler.

Ved modellering kvantificerer vi den langsigtede effekt af skovhugst på kulstoflagrene, især på AGC og dødt ved. Høj hugstintensitet (50% reduktion af oprindelige biomasse) reducerede samlede kulstoflagre med 27%. Genopbygningen af AGC var lavere ved høje hugstintensiteter, hvilket tyder på nedsat resiliens. Derfor bør man overveje at holde hugstintensiteten, f.eks. under 20%, for at begrænse den langsigtede effekt af hugst på AGC og dødt ved.

**Nøgleord**: Overjordisk biomasse; underjordisk biomasse; dødt ved; Dipterocarp skov; førne; skovdrift; jordens organisk kulstof

# Publications

***Published***

**Rozak, A.H.**, E. Rutishauser, K. Raulund-Rasmussen, P. Sist. 2018. The imprint of logging on tropical carbon stocks: A Bornean case study. Forest Ecology and Management 417: 154-166. DOI: 10.1016/j.foreco.2018.03.007

***Manuscript under review in Forest Ecosystems***

**Rozak, A.H.**, E. Rutishauser, P. Sist. How do we estimate deadwood stocks in disturbed forests? A carbon stocks assessment study in Bornean logged forests

***Manuscript to be submitted to Plant and Soil***

**Rozak, A.H.**, E. Rutishauser, K. Raulund-Rasmussen, V. Freycon, P. Sist. Depletion of soil organic carbon stocks in Bornean logged forests.

***Communication in conference***

a. **Rozak, A.H.**, K. Raulund-Rasmussen, V. Freycon, P. Sist, E. Rutishauser. 2017. Logging intensity, litter, and slope drive soil organic carbon variability in Dipterocarp logged forests. BES, GFÖ, NECOV and EEF Joint Annual Meeting: Ecology Across Borders. Ghent (Belgium): 11-14 December 2017. Oral presentation.
b. **Rozak, A.H.**, P. Sist, E. Rutishauser. 2016. Deadwood in logged-over Dipterocarp forests of Borneo. The 53rd Annual Meeting of the Association for Tropical Biology and Conservation (ATBC). Montpellier (France): 19-23 June 2016. Oral presentation.

***Workshop***

Tropical forest biodiversity and carbon storage: Developing a roadmap for a long-term forest monitoring network in Indonesia. Organized by Manchester Metropolitan University (United Kingdom) and Forest Research and Development Centre, Ministry of Environment and Forestry (Indonesia). Bogor 13-16 September 2016. **Output**: Brearly, F.Q., W.C. Adinugroho, F. Aini, ..., **A.H. Rozak**, ..., C.O. Webb. *Opportunities and challenges for an Indonesian forest-monitoring network*. Manuscript is under review in Forest Ecosystems (special issue: National Forest Inventories).

The contribution of Andes Hamuraby Rozak to the papers included in this thesis:
Rozak contributed to the research design, data collection in the field, data analysis, interpretation of the results, and writing the text for all papers (Chapter 2, 3, and 5).

# 1
# General introduction

*One of the main pressures faced by Bornean forest i.e. forest conversion to a non-forest land-use type such as industrial plantation and coal mining. This picture shows the borders between coal mining area and a Dipterocarp forest nearby Malinau Research Forests (North Kalimantan).*

*(Picture by Andes Hamuraby Rozak)*

## 1.1. Tropical forests and carbon issue

While tropical forests only represent 12% of the global land surface (Keenan et al. 2015), they are estimated to be home for more than half of all known species (Dirzo and Raven 2003b; Wright 2005). They also provide important societal and environmental functions, such as timber production (e.g. Keller et al. 2007; Sasaki, Chheng, and Ty 2012), climate regulation (e.g. Bawa and Markham 1995; Bonan 2008) as well as nutrient and carbon (C) cycling (e.g. Baccini et al. 2017; Le Quéré et al. 2018; Malhi 2012; Qie et al. 2017; Vitousek and Sanford 1986). Trees are the most emblematic feature of tropical forests, forming a subtle interface between the ground and the atmosphere. Through photosynthesis, trees are sequestering C above ground in their trunk, branches, and leaves (also known as above-ground biomass, AGB), and below ground in their roots (referred to as below-ground biomass, BGB). Trees are also the important source of organic carbon in the soil (SOC) through root exudation which can account for up to 10% of total photosynthetic production (Jones, Hodge, and Kuzyakov 2004; Jones, Nguyen, and Finlay 2009). When trees die, biomass generally decomposes within a few decades (Hérault et al. 2010; Chambers et al. 2000), and contribute to form large stocks of deadwood (Pfeifer et al. 2015; Osone et al. 2016). While most of this organic material is re-emitted to the atmosphere through microbial respiration, a small fraction enters soils and enriches the SOC. Summing up the C stored in these different pools at landscape scale places tropical forests among the C-richest ecosystems (Pan et al. 2011). Indeed, tropical forests are estimated to store *c.* 250 Gt C in living trees (Saatchi et al. 2011) and account for 40 Pg C $yr^{-1}$ (or 35%) of terrestrial gross primary productivity (Beer et al. 2010).

Despite all the benefits delivered by tropical forests, they are still disappearing or being depleted at high rates due to anthropogenic activities (Achard et al. 2014; Baccini et al. 2017; Potapov et al. 2017). Tropical forests contribute approx. 30% of global forest cover loss, at a rate increasing by 0.2 million ha $yr^{-1}$ from 2000 to 2012[1] (Hansen et al. 2013). The proximate cause of deforestation is a combination of agricultural expansion and infrastructure expansion (Geist and Lambin 2002; Lambin et al. 2001). In addition to deforestation, tropical forests are being degraded through timber harvesting, uncontrolled fires, and wood fuel/charcoal (Hosonuma et al. 2012). Lumping together, forest conversion to agriculture, forestry and forest degradation is responsible for about a quarter of anthropogenic greenhouse gas emission (IPCC 2014).

Agriculture, Forestry and Other Land Use (AFOLU) have contributed significantly to greenhouse gas emissions during 1970-2010 (IPCC 2014). In 2010 particularly, AFOLU represented 25% (approx. 12 Tg $CO_2$-eq) of total annual anthropogenic emissions. For 2007-2016, C emissions from land-use, land-use change, and forestry were estimated to be 1.3 Gt C $yr^{-1}$ or approx. 10% of the global C emissions (Le Quéré et al. 2018). Emissions from

[1] According to Hansen et al. (2013): (1) Brazil exhibited the largest decline in annual forest loss, with a high of over 4 million ha $yr^{-1}$ (2003-2004) and a low under 2 million ha $yr^{-1}$ (2010-2011), and (2) Indonesia exhibited the largest increase in annual forest loss, with a low under 1 million ha $yr^{-1}$ (2000-2003) and a high of over 2 million ha $yr^{-1}$ (2011-2012).

deforestation and forest degradation (including logging) represent respectively 70% and 30% of AGC losses in tropical forests (Baccini et al. 2017), but varies regionally. For instance, in tropical Asia, forest degradation from the forestry sector was estimated to form up to 45% of total C emissions emitted annually in the region, of which 50% is due to logging activities.

In order to tackle C emissions due to AFOLU, the Reducing Emissions from Deforestation and forest Degradation (REDD) scheme was initiated in 2007 by the parties of the United Nations Framework Convention on Climate Change (UNFCCC) (Hein et al. 2018; Hein and van der Meer 2012). REDD+ is a beam of actions that promotes sustainable forest management (SFM), conservation, and enhancement of forest C stocks. REDD+ goes through financial incentives in countries able to prevent the exploitation or conversion of tropical forests into more lucrative land-uses. A key concept lies into sustainable forest management (SFM), broadly defined as "the process of managing forest to achieve one or more clearly specified objectives of management with regard to the production of a continuous flow of desired forest products and services without undue reduction of its inherent values and future productivity and without undue undesirable effects on the physical and social environment" (ITTO 2005). SFM practices, such as reduced-impact logging, were shown to have several advantages over conventional logging practices, notably in reducing C emissions. For instance, switching from conventional (CVL) to reduced-impact logging (RIL) in tropical production forests could reduce C emissions by 30-50% (approx. 1.5-2.1 Gg $CO2\ yr^{-1}$) while maintaining the level of production (approx. 166-280 $m^3$ of end-use wood) under a 50-yr cycle (e.g. Sasaki et al. 2016; Sasaki, Chheng, and Ty 2012). Unfortunately, RIL is not widely employed by logging industry and still has its own challenges to be solved (such as technical capacity and the enforcement of regulatory in each country) to achieve SFM, especially in tropical production forests (Nasi and Frost 2009; Putz, Sist, et al. 2008; Schulze, Grogan, and Vidal 2008).

## 1.2. On the importance of production forests

Production forests refer to forests designated primarily for production of timber, fiber, bio-energy, and/or non-wood forest products (FAO 2010). In tropical regions, the selective harvest of a few commercial species is the dominant practice (Putz, Sist, et al. 2008; Sist, Garcia-Fernandez, and Fredericksen 2008; Sist, Fimbel, et al. 2003). In 2010, about half of the remaining tropical forests was designated for timber production (approx. 400 million ha from a total of 780 million ha of permanent tropical forest estate, Blaser et al. 2011). From 2005 to 2010, the area of production forests in tropical regions increased by 50 million ha. Recently, logged and secondary forests have become an increasingly prominent feature of tropical landscapes and now account for a majority of the remaining forest cover in many regions. Several studies have highlighted the importance of these forests in maintaining ecosystem function and services (Edwards, Tobias, et al. 2014), notably in maintaining biodiversity (e.g. Edwards et al. 2011; Edwards, Magrach, et al. 2014; Costantini, Edwards, and Simons 2016) and affecting C stocks (e.g. Martin et al. 2015; Sist et al. 2014; Khun and Sasaki 2014a).

Commercial logging directly affects C stocks through the direct harvest of large stems and killing/smashing on non-target trees (i.e. incidental damages). By creating large gaps in the canopy, microclimates change locally (Gaudio et al. 2017; Hardwick et al. 2015) and speed up the decomposition of litter (Salinas et al. 2011) and soil organic matter (Covington 1981; Fontaine et al. 2004; Raich et al. 2006). In African tropical forests, soil organic carbon content (until 100 cm depth) was shown to be strongly affected by logging, continuing to lose C up to 45 years after logging (Chiti et al. 2015). In Amazonian forests, Berenguer et al. (2014) reported contrasting results on the effect of logging on SOC in the upper layers (until depth 30 cm): (1) in Paragominas, the stocks were higher in logged (63 Mg C $ha^{-1}$) compared to intact forests (43 Mg C $ha^{-1}$), while (2) in Santerém, the stocks were comparable between logged (55 Mg C $ha^{-1}$) and intact forests (57 Mg C $ha^{-1}$).

The degree of forest damage, as well as the speed of C recovery, was shown to be primarily related to logging intensity (Piponiot et al. 2016; Rutishauser et al. 2015; Sist, Sheil, et al. 2003; Sist and Nguyen-Thé 2002). Above-ground C stocks recover over time through the growth of survivors and recruited trees. In Amazonia, time of recovery was shown to primarily depend on logging intensity (Rutishauser et al. 2015). Accounting for both the biomass harvested and lost due to incidental damages, Rutishauser et al. (2015) found that a 25% reduction of pre-logging AGC stock would require approx. 43 years to recover its initial value in Amazonian forests. However, even though AGC increases through tree growth post-logging, poor logging practices or high logging intensity may induce large incidental damages among non-target trees (Shenkin et al. 2015; Sist and Nguyen-Thé 2002; Sist, Sheil, et al. 2003), and generate lagged mortality of injured trees over a few decades (Blanc et al. 2009, Lussetti et al 2016). Increased mortality could potentially increase deadwood stocks (Figure 1-1) and result in negative carbon net change (Blanc et al. 2009). The persistence of increased deadwood stocks remains to be demonstrated, but will depend on decomposition rates that were shown to vary with tree species and trunk diameter (Harmon et al. 1995; Hérault et al. 2010).

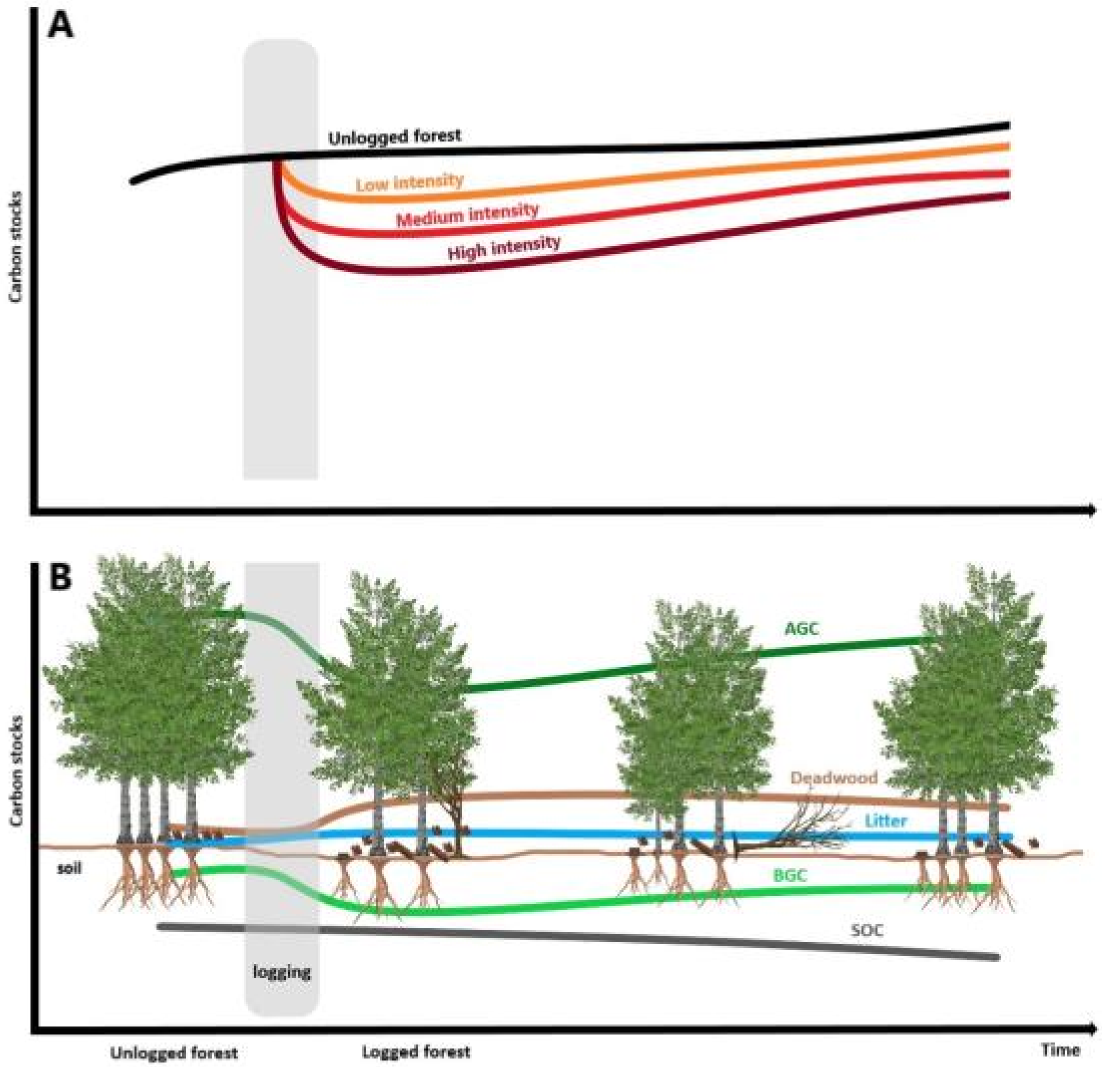


*Figure 1-1 Hypothesized effect of logging intensity on C stocks under different logging intensities (A) and hypothesized of the dynamic of each C pool following logging (B). Lines in panel B show the dynamic of each C pool along time.*

As shown above, tropical forests may either be a source or sink of C driven by the magnitude of post-logging mortality and regrowth. When logged or managed, forests tend to become a net source while short after logging, and returning to no net change after a few decades (Blanc et al. 2009). Long-term C dynamics in managed forests are driven by several variables, such as logging techniques (Pinard and Cropper 2000; Sasaki et al. 2016; Sasaki, Chheng, and Ty 2012), logging intensity (Piponiot et al. 2016; Rutishauser et al. 2015), and environmental factors (Vieira et al. 2004; Piponiot et al. 2016). Understanding the recovery of C stocks and long-term C balance in managed forests is fundamental to attest their environmental and social contribution and avoid future conversion.

## 1.3. Assessing C stocks in tropical forests

Searching with a Boolean operator (as explained in Figure 1-2) in ISI Web of Science and Scopus databases, sixty-nine studies assessing C stocks in tropical forests were found. Logged forests represent about a third (25 studies) of all studies. The majority (32 studies) are located in tropical America. Generally, the number of studies assessing total C stocks (i.e. the sum of AGC, BGC, deadwood, litter, and SOC) is higher in intact than in logged forests, disregarding the logging intensity and time since logging. The mean proportion of AGC to total C stocks are higher in intact than in logged forests (55% vs 43%, respectively), while deadwood stocks are higher in logged forest than in intact forests (10% vs 25%, respectively). It results that total C stocks in intact forests is higher than in logged forests but the mean difference is only about 20 Mg C $ha^{-1}$ (340 and 320 Mg C $ha^{-1}$ in intact and logged forest, respectively). C pools are highly variable in intact and logged forest, especially deadwood stocks (Figure 1-2C). This variability is likely explained by differences of management regime (such harvest intensity as well as logging techniques) and environmental conditions (such as climate and soils) among studies.

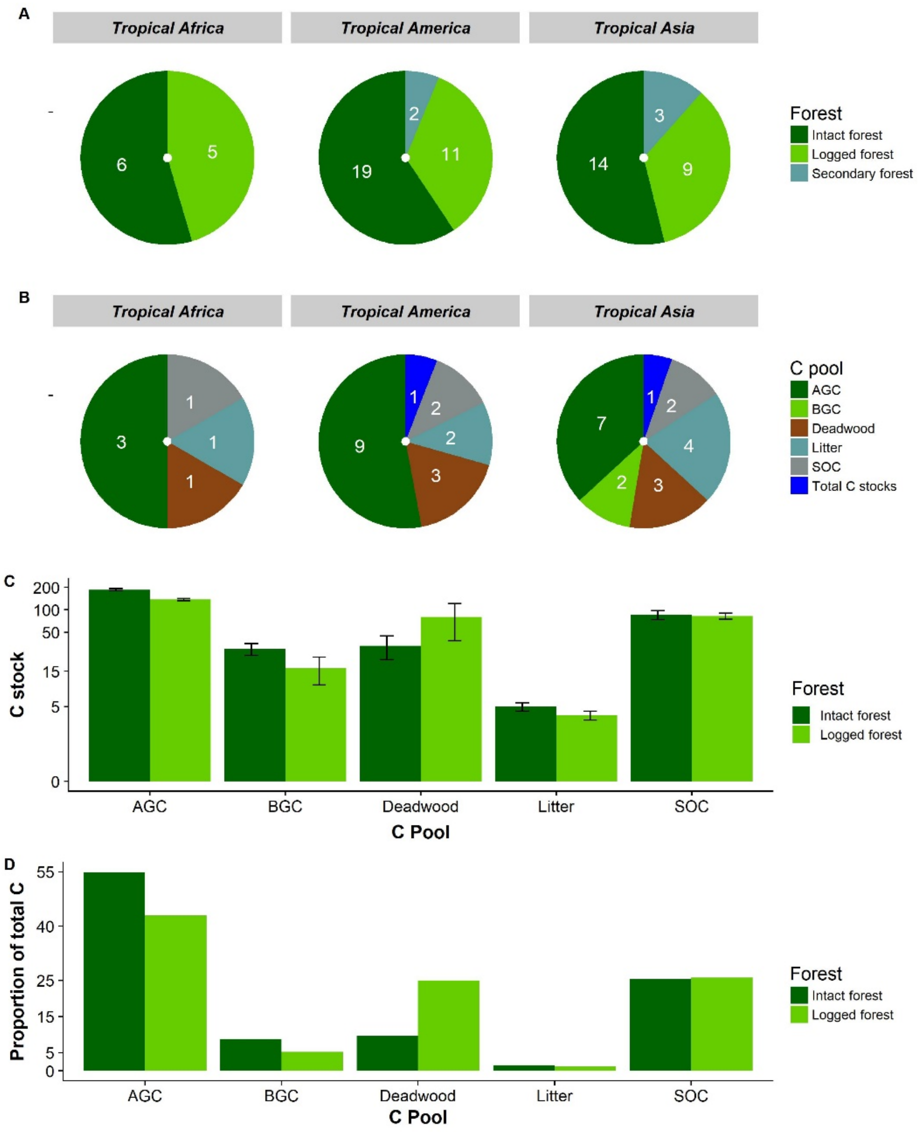


*Figure 1-2 Studies on C stocks in tropical forests based on literature searches in ISI Web of Science and Scopus database. Panel A shows the number of C stock studies in intact, logged, and secondary forests (n = 69 studies). The Boolean operators used for panel A was tropical forest AND (carbon stock OR deadwood stock OR litter OR soil organic carbon OR coarse woody debris OR above ground biomass). Panel B shows the breakdown studies on each C pool and total C stocks (AGC, BGC, deadwood, litter, and SOC) in logged forests (n = 25 studies). The Boolean operators used for panel B was: (selective logging OR reduced impact logging OR conventional logging OR logging intensity OR degraded forest) AND tropical forest AND (carbon stock OR deadwood stock OR litter OR soil organic carbon OR coarse woody debris OR above ground biomass). Panel A and B only show field-based studies, excluding modeling and remote sensing studies. Panel C shows a comparison of the average value of each C pool (Mg C ha$^{-1}$) between intact and logged forests., Panel D shows the proportion of each C pool (%) to total C stocks. The white font numbers (panels A and B) show the number of studies for each pie. The error bars in panel C indicate one standard error of the mean (Mg C ha$^{-1}$ ± SE).*

Most studies on C stocks aimed to compare specific C pool or total C stocks between logged and unlogged forests, or in comparison with other land-use types such as secondary forests or palm oil plantations (Table 1-2). Further, most studies on C stocks also only considered logged forests as a whole and did not specifically consider logging intensity as the variable tested in their studies whereas this variable is a main driver influencing forest damage and C recovery (Piponiot et al. 2016; Rutishauser et al. 2015; Sist and Nguyen-Thé 2002). However, to quantify C pools in logged forests is challenging because the tree-level process of growth and death, litter production, deadwood stocks, and SOC stocks are difficult to assess with a satellite-based system (Houghton, Hall, and Goetz 2009). Even though a more advanced remote sensing technique will be launched around 2020 through the BIOMASS mission (Le Toan et al. 2011; Scipal et al. 2010), this mission will only assess above-ground biomass excluding the other C pools that contribute around 35% to total C budget (Saner et al. 2012). Further, to tracked back logging history as well as prelogging data is difficult especially, for example, in a logging concession in Indonesia.

*Table 1-1 Selected studies examining the effect of logging on each C pool and total C stocks in tropical forests. Total C stocks define as the sum of above- and below ground C (AGC and BGC), deadwood C, litter C, and soil organic carbon (SOC).*

| **Reference** | **Region** | **Location** | **Purpose of the study** | **Time after logging** | **C pool examined** |
|---|---|---|---|---|---|
| **(Saner et al. 2012)** | SE Asia | Sabah, Malaysia | To estimate impacts of logging on the C balance;<br>To compare C stocks between logged forests and unlogged forests | 22 years | Total C stocks |
| **(Osone et al. 2016)** | SE Asia | Bukit Soeharto, East Kalimantan | To investigate the combined effects of fire and logging intensity on deadwood stocks | 1 month, 15 years | Deadwood, AGC |
| **(Kenzo et al. 2015)** | SE Asia | Sabah, Malaysia | To assess the forest structure and AGB in logged forests and other forest types in the region;<br>To assess how forest structure and AGB differ between logged forests growing on infertile and fertile soils | 20 years | AGC, BGC, litter |
| **(Pfeifer et al. 2015)** | SE Asia | Sabah, Malaysia | To estimate deadwood stocks and their relative contribution to AGC;<br>To investigate the variation of deadwood stocks and linked to forest attributes | 22 years | AGC, deadwood |
| **(Prasetyo et al. 2015)** | SE Asia | Central Kalimantan, Indonesia | To monitor litter production in various periods of logging and primary forest | 1, 5, 10 years | Litter |
| **(Morel et al. 2011)** | SE Asia | Sabah, Malaysia | To present mean C stock values for different land-cover types across Sabah;<br>To investigate the potential for ALIS-PALSAR data to differentiate oil palm plantation from forest area; | 1, 5, 8, 18, 20, 38 years | AGC |

| Reference | Region | Location | Purpose of the study | Time after logging | C pool examined |
|---|---|---|---|---|---|
| | | | To assess generated logarithmic relationships between AGB and SAR back-scatter for estimating AGB across Sabah | | |
| **(Bryan et al. 2010)** | Papua New Guinea | Makapa, PNG | To quantify forest biomass in logged and unlogged forests, and losses caused by RIL practices at the landscape scale | 10 years | AGC |
| **(Lasco et al. 2006)** | SE Asia | Mindanao, Philippines | To determine AGC and BGC of the various stages of forest cover after logging;<br>To analyze the C budget of the sawmill and the veneer/plywood plant | 1-5, 6-10, 11-15, 16-20, 21+ years | AGC, litter, SOC |
| **(Pinard and Putz 1996)** | SE Asia | Ulu Segama, Malaysia | To describe forest biomass stores both before and after logging;<br>To compare logging damage between conventional logging and RIL;<br>To quantify the C retained in biomass due to the implementation of the harvesting guidelines | 3 months, 8-12 months, 12 months | AGC |
| **(Berenguer et al. 2014)** | America | Sanatrém-Belterra and Paragominas, Brazil | To evaluate the effects of anthropogenic forest disturbance (from selective logging, fire, and fragmentation) on C stocks | 6-22 years | Total C stocks |
| **(van der Sande et al. 2018)** | America | Pibiri, Guyana | To test the effects of abiotic and biotic factors on biomass stocks, SOC, and productivity | 1, 6 years (AGB).<br>19 years (litter, SOC) | AGC, litter, SOC |
| **(Roopsind et al. 2017)** | America | Suriname | To assess the recovery of AGC and timber stocks after selective logging | 32 years | AGC |
| **(Vidal, West, and Putz 2016)** | America | Eastern Brazil | To evaluate the effects of conventional logging and RIL on bole volume recovery of merchantable species recovery | 20 years | AGC |
| **(Piponiot et al. 2016)** | America | Amazon Basin and the Guiana Shield | To detect the main drivers and patterns of AGC recovery in logged forests;<br>To model the trajectory of AGC changes over time | 0-30 years | AGC |
| **(Rutishauser et al. 2015)** | America | Amazon Basin | To assess the main drivers of time-to-recovery of post-logging tree C | | AGC |

| Reference | Region | Location | Purpose of the study | Time after logging | C pool examined |
|---|---|---|---|---|---|
| **(Sist et al. 2014)** | America | Paragominas, Brazil | To investigate the effect of logging on AGB dynamics and among tree diameter size classes;<br>To propose specific recommendations to improve forest management and reduce C emissions | 8 years | AGC |
| **(Mazzei et al. 2010)** | America | Paragominas, Brazil | To assess the contribution of growth, mortality, and recruitment to AGB;<br>To predict the time needed to recover its initial AGB after RIL;<br>To propose silvicultural recommendations related to logging intensity and allowable damage rates to improve biomass recovery in selectively logged forests | 3 months, 1, 2, 4 years | AGC |
| **(Blanc et al. 2009)** | America | French Guiana | To examine the contribution of tree growth and recruitment vs tree harvesting and death to changes in AGC fluxes over 20 years;<br>To extrapolate the long-term consequences of differences in forest dynamics after logging to AGC balance | 20 years | AGC |
| **(Palace et al. 2007)** | America | Juruena and Tapajos, Brazil | To examine the effect of RIL to deadwood pool compared to undisturbed forest | 1 year | Deadwood |
| **(Keller et al. 2004)** | America | Cauaxi and Tapajos, Brazil | To quantify deadwood mass in logged and unlogged forests;<br>To quantify the generation of deadwood by both conventional logging and RIL management | 1 years | Deadwood |
| **(Tchiadje et al. 2016)** | Africa | Cameroon | To quantify the biomass that is lost in each step of post-felling activities | Just after logging | AGC |
| **(Carlson et al. 2016)** | Africa | Gabon | To quantify and evaluate the drivers of deadwood in logged and unlogged forests | Na | Deadwood |
| **(Chiti et al. 2015)** | Africa | Ghana, Cameroon, Gabon | To evaluate the effect of selective logging on the SOC levels in intact forests;<br>To evaluate whether the assessment of SOC changes due to selective logging is relevant in the | 10, 15, 18, 30, 45, 50 years | SOC, litter |

| Reference | Region | Location | Purpose of the study | Time after logging | C pool examined |
|---|---|---|---|---|---|
| | | | framework of REDD+ | | |
| **(Gourlet-Fleury et al. 2013)** | Africa | M'Baiki, Central Africa | To quantify the response of AGB and timber stock to the treatments over of 24 years;<br>To examine the speed of the forest recovery in relation to the logging intensity and the effect of thinning on recovery | 24 years | AGC |
| **(Medjibe et al. 2011)** | Africa | Monts de Cristal, Gabon | To assess the consequences of low-intensity RIL on AGB and tree species richness | Just after logging | AGC |

To conclude, most of C stocks studies in tropical rainforest mainly focus on the individual component of the total C stocks (Table 1-2). We still have a limited understanding of all C pools (AGC, BGC, deadwood, litter, and SOC) notably in forest experiencing human-induced disturbance such as a logged forest. To our knowledge, we found only one study of total C stocks in tropical logged forests of Asia (Saner et al. 2012) and one in tropical logged forests of America (Berenguer et al. 2014). We also have very few C studies in tropical logged forests of Africa (Table 1-2). Further, no such total C stocks studies investigate the impact of logging intensity which is the main factor influencing AGC dynamic in logged forests. Particularly in Bornean logged forests, studies assessing the long-term impact of logging on the five C pools remain rare. Experimental evidence on C study, especially in Indonesian Borneo, is weak because long-term studies are scarce and few experimental sites exist in logged forests (Sist et al. 2015). Especially in production forests of Indonesia, there are, so far, only two experimental sites that well recorded logging history, prelogging data, and post-logging data i.e. STREK (in Berau, East Kalimantan, see Bertault and Kadir 1998) and MRF plots (in Malinau, North Kalimantan, see CIFOR and ITTO 2002). However, most of the data only comprise living trees, while deadwood, litter, and soil organic C are still lacking. Although these three C pools represent a low stocks and proportion of the total C stocks (Saner et al. 2012), they can have an important contribution in C emissions at a regional or global scale and therefore can have significantly impact to the future of atmospheric $CO_2$ concentration (Houghton 2012; Houghton, Byers, and Nassikas 2015). Extrapolated to 11 million ha of Indonesian Bornean logged forests (Gaveau et al. 2014), a small loss of 2 Mg C $ha^{-1}$ from the soil will lead to the loss of approx. 22 Tg C (1 Tg = $10^6$ Mg). Therefore, considering that 400 million ha are designated by national forest departments for timber production (Blaser et al. 2011) and these logged forests play an important role for economic growth of many tropical countries such as Indonesia (ITTO 2015), studies on the impact of logging on C stocks, particularly the impact of logging intensity, are needed. A better understanding of the effect of logging intensity on C pools will allow silvicultural practices aiming to limit the negative impact of logging on C storage to be defined. This study aims to fill this gap and give new insights on the long-term impact of logging intensity on the major C pools in a managed forest.

## 1.4. Methods to estimate C stocks in tropical forests

The Intergovernmental Panel on Climate Change (IPCC) guidelines for national greenhouse gas inventories (IPCC 2006) recommend to quantify the major ecosystem C stocks: above-ground (AGC) and below-ground (BGC) in living trees, dead organic matter (deadwood and litter), and soil organic carbon (SOC). However, AGC (DBH >10 cm) has received more attention than any other C pools in both intact or logged forests. This is due to the fact that it represents the largest fraction, most visible, and most easily measurable.

Above-ground biomass (AGB, i.e. biomass in living trees) is generally estimated through allometric models. With increasing attention paid to forest C stocks, new allometric models are becoming available, lowering uncertainties surrounding AGB estimates. Generic allometric models including tree height, DBH, wood specific gravity, and local bioclimatic variable are now available and were shown to be more accurate that models based on DBH alone (Chave et al. 2014). At Borneo, the use of such generic allometric models was shown to reduce uncertainty over existing local models (Rutishauser et al. 2013). For this reason, we opted to work with the most recent equation developed by Chave and collaborators to estimate tree AGB at our study sites. Another major pool of biomass is found below-ground, as large and fine roots, referred hereafter to as below-ground biomass (BGB). In this study, we used a recent allometric model relating BGB to tree diameter in a Dipterocarp forest of Peninsular Malaysia (Niiyama et al. 2010).

The other C pools (i.e. deadwood, litter, and SOC) are generally disregarded due to the tediousness and high cost of measurement. However, these three components can form up to 35% of total C stocks (Berenguer et al. 2014; Saner et al. 2012). For sake of simplicity, these stocks are generally merely estimated through an expansion factor based on AGC (e.g. Carlson et al. 2016; Chao et al. 2009; Lewis et al. 2009). For example, Carlson et al. (2016) used a fixed ratio of 12% of AGC to estimate deadwood in African logged forests. Further, the use of expansion factor or default factor (especially for Tier 1, Table 1-3) from AGC to deadwood and litter stocks is also recommended by UNFCCC (2015). However, the use of expansion factor at global scale remains hazardous as C pools are highly variable especially in degraded forests (Osone et al. 2016; Pfeifer et al. 2015). For example, the ratio of deadwood/AGC was found to range between 40% to 200% in Bornean disturbed forests (Osone et al. 2016).

*Table 1-2 Conservative default factor for estimating deadwood ($DF_{Deadwood}$) and litter ($DF_{Litter}$) stocks as a percentage of AGC for tropical forests. Values were extracted from UNFCCC (2015).*

| ***Elevation (m)*** | ***Precipitation (mm yr$^{-1}$)*** | ***$DF_{Deadwood}$*** | ***$DF_{Litter}$*** |
|---|---|---|---|
| **<2000** | <1000 | 2% | 4% |
| **<2000** | 1000-1600 | 1% | 1% |

| | | | |
|---|---|---|---|
| **<2000** | >1600 | 6% | 1% |
| **<2000** | All | 7% | 1% |

Two recognized methods are used worldwide to estimate deadwood stocks i.e. line-intersect sampling (LIS, Van Wagner 1968; Warren and Olsen 1964) and fixed area sampling (FAS, Gove and Deusen 2011; Harmon and Sexton 1996). LIS is a probability-proportional-to length sampling method and consist of one or more transect lines along which all intersecting down deadwood with the transect line above a given diameter are measured. FAS is based frequency of occurrence of each individual deadwood (either down or standing deadwood) within a given area where the dimension of each deadwood within the sample unit are measured. With respect to their assumption, especially for LIS, those two methods have their own pros and cons (Russell et al. 2015). However, even though both methods result in different estimation for down deadwood stocks (Baker et al. 2007; Jordan, Ducey, and Gove 2004), due to its simplicity and efficiency, recent protocols on deadwood measurement combine LIS (for down deadwood) and FAS (for standing deadwood) to estimate deadwood stocks (e.g. Marthews et al. 2012; Walker et al. 2014). Further, several studies using different methodologies to estimate deadwood volumes such as Smalian's, average-of-ends or conical frustums equations (Berenguer et al. 2014; Palace et al. 2007; Pfeifer et al. 2015; Saner et al. 2012). Those equations result under- or over-estimate than using a recently developed equation which is a conic-paraboloid model (Fraver, Ringvall, and Jonsson 2007). For example, Smalian's (as used in Berenguer et al. 2014) or conical frustum (as used in Pfeifer et al. 2015) result in +12% and -8% bias, respectively. In this study, we specifically compared LIS and FAS methods simultaneously with the use of dynamic penetrometer and decay classification to estimate each specific deadwood density.

For soil organic matter estimation, the use of the wet combustion instead of the dry combustion method to estimate C concentration in the soil influences the estimation of soil organic carbon (SOC) stocks which contribute a significant portion to total ecosystem C stocks that reach in average 50% in tropical forests (Lal 2005). The wet digestion method (Walkley and Black 1934) was found significantly underestimating compared to the dry combustion method because its only oxidized the most active organic carbon (Allison 1960) although a high correlation is found between these two methods (De Vos et al. 2007; Jankauskas et al. 2006; Lettens et al. 2007; Meersmans, Van Wesemael, and Van Molle 2009). However, the wet combustion method is still widely used worldwide because it is simple, rapid, cheap, and present minimal equipment needs (Tivet et al. 2012). To avoid methodological biases, the use of correction factors (De Vos et al. 2007; Krishan et al. 2009; Mikhailova, Noble, and Post 2003) for SOC estimation are suggested, but these factors depend on the character of the organic matter which again depends on land-use type, soil texture, and depth (Tivet et al. 2012). In this study, we used the wet combustion method due to the lack of equipment and time.

## 1.5. The overview of the Bornean forest

The island of Borneo is the largest island in South-East Asia and is shared between 3 countries Indonesia, Malaysia, and Brunei. In 2010, forest area including degraded, managed and intact forests represented about 53% of the total areas of the island (Gaveau et al. 2014) (Figure 1-3). Forests of Borneo as in the entire Malesia region, are dominated by the Dipterocarpaceae family. The Dipterocarpaceae is a family amongst the tallest trees found in the Bornean lowland forests (Appanah and Turnbull 1998; Ashton 1983; Banin et al. 2012; Whitmore 1984). The family gathers about 695 species (Christenhusz and Byng 2016) and approx. 267 species are found in Bornean forests (Ashton 1983; Brearley, Banin, and Saner 2016; Whitmore 1984). This taxon is the most dominant family in the island followed by Euphorbiaceae with 22% and 12% of all trees (DBH ≥9.8 cm), respectively (Slik et al. 2003). Due to its dominance both in terms of stems (up to 25% of the total tree density) and basal area (often 50% of the total basal area), forests dominated by Dipterocarpaceae are called mixed Dipterocarp forests (Whitmore 1984). Shorea and Dipterocarpus are the most abundant genera of the family Dipterocarp forests (Slik et al. 2003) and are the common Dipterocarpaceae tree species harvested in the island as it produces long, straight, and knot free logs which are ideal for the timber industry (FAO 2016).

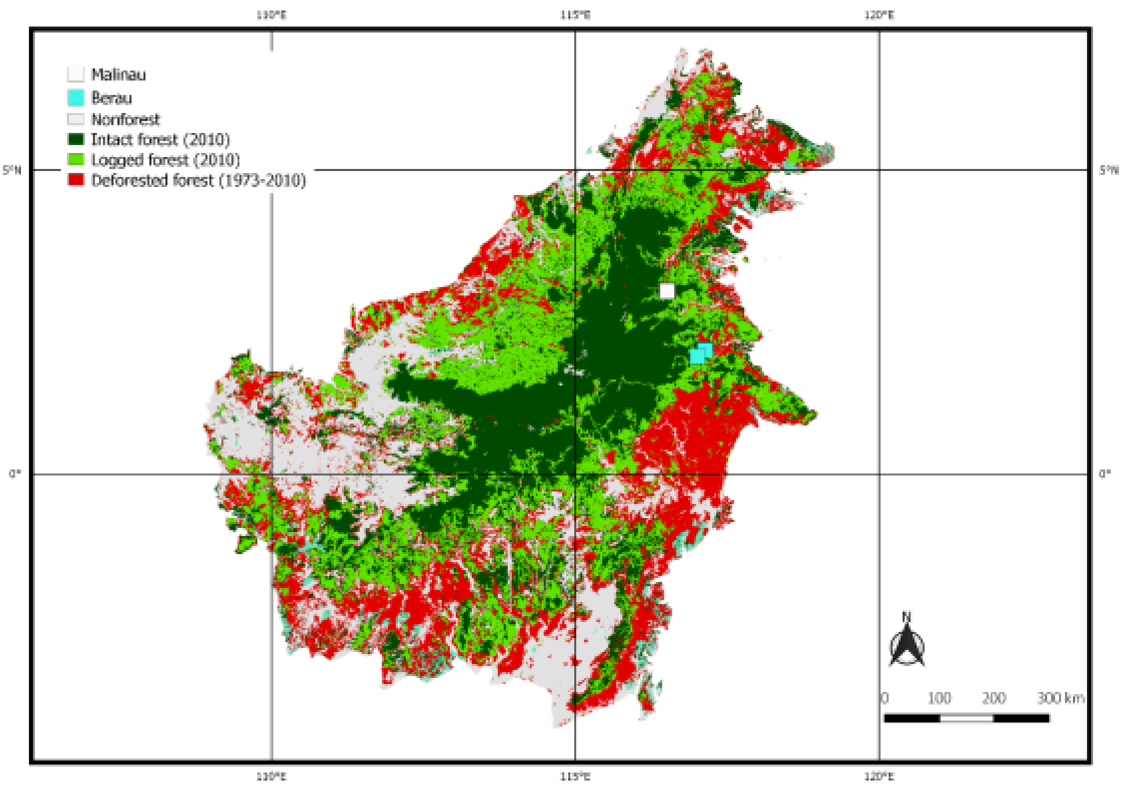


*Figure 1-3 Forest status in Borneo based on Gaveau et al. (2014). Study sites of this thesis are in Malinau (white box) and Berau (blue boxes).*

Most of the forests in Borneo are under intense pressure and threatened by anthropogenic activities such as logging, and conversion to monoculture plantation and mining industry (Gaveau et al. 2014; Nasi and Frost 2009; Sodhi et al. 2009; Wilcove et al. 2013). Those activities result in a detrimental impact on SE Asia's biodiversity (Sodhi et al. 2009) and the shrinkage of intact forests (Gaveau et al. 2014) that are essential for biodiversity conservation (e.g. Barlow et al. 2007; Gibson et al. 2011; Hughes, Daily, and Ehrlich 2002). During 1973-2010, forests in Indonesian Borneo have lost about 30% or equivalent to 12.4 million ha (Table 1-1). Gaveau et al. (2014) identified around 21 million ha of intact forests of which 8.8 million ha (approx. 42% of the intact forests) fall within the production forests land-use class and prone to be logged in the near future and 3.4 million ha (approx. 16% of the intact forests) to be converted to other land-uses. Assuming that all production forests are logged, and areas designated for conversion are converted, logged forests will be the main land-use class in the islands with 26.8 million ha (approx. 36% of the total land area) followed by intact forests with 8.8 million ha (approx. 16% of the total area). Therefore, logged forests will play crucial roles in the trade-off between the provision of goods (timber, rattan, food, etc.) and maintenance of C stocks, biodiversity, and other ecosystem services (Meijaard and Sheil 2007; Sist et al. 2015). Although protected areas in the island cover about 6.6 million ha (Proctor, McClean, and Hill 2011), these areas still impacted by deforestation through forest conversion or forest degradation (Curran et al. 2004).

*Table 1-3 Summary of forest area in Borneo in the year 1973 and 2010 (in million ha). Data were extracted from Gaveau et al. (2014).*

| | **Borneo** | **Kalimantan** | **Brunei** | **Sabah** | **Sarawak** |
|---|---|---|---|---|---|
| **Total land area** | 73.7 | 53.3 | 0.6 | 7.4 | 12.4 |
| **Forest area in 1973** | 55.8 | 40.4 | 0.5 | 5.8 | 9.2 |
| **Intact forest area in 2010** | 21 | 17.4 | 0.3 | 1.4 | 1.8 |
| **Logged forest area in 2010** | 18 | 10.6 | 0.1 | 2.1 | 5.3 |
| **Forest area loss 1973-2010** | 16.9 | 12.4 | 0.04 | 2.3 | 2.1 |
| **Forest area loss 1973-2010 (%)** | 30.2 | 30.7 | 8.4 | 39.5 | 23.1 |

### 1.5.1 Logging practices in Borneo

Mixed Dipterocarp forests in Borneo have long been exploited for timber production in SE Asia (Nasi and Frost 2009; Nicholson 1979), unfortunately with a poor implementation of sustainable forest management practices. In the 1990s, three innovative logging guidelines, one published by International Tropical Timber Organization (ITTO) namely *the ITTO Guidelines for Sustainable Management of Natural Tropical Forests Management* (1992) and the two others published by Food and Agricultural Organization (FAO) namely *the FAO Model Code of Forest Harvesting Practice* (Dykstra and Heinrich 1996) and *the FAO Code of Practice for Harvesting in Asia-Pacific* (1999), were released in order to support sustainable forest management. At the same time, with increasing awareness for tropical forests, Indonesia and Malaysia went further developed their own guidelines to complement the ITTO guideline.

Particularly in Indonesia, extensive research on how to reduce forest damage and minimizing the effect of logging through reduced-impact logging (RIL) was carried out in Berau (East Kalimantan) and followed in Malinau (North Kalimantan, formerly East Kalimantan) (Sist, Sheil, et al. 2003; Sist et al. 1998; Sist and Nguyen-Thé 2002). The studies demonstrated that RIL techniques under moderate logging intensities (8 trees harvested ha$^{-1}$) could reduce forest damage significantly. Sist et al. (1998) reported that RIL reduced damage by 50% compared with conventional logging (CVL) in Berau but the damage was dependent on logging intensity. Further, in the case of Malaysian production forests, Pinard and Putz (1996) reported that one year after logging, forests harvested by RIL have 67% of the biomass of pre-logging levels compared with 44% of biomass when CVL was applied. With regards to C stocks, Putz et al. (2008) reported that using an improved timber harvesting (RIL) practices would retain at least 0.16 Gt C year$^{-1}$, and predicted to be at least 30 Mg ha$^{-1}$ higher than those conventionally logged due to reduced collateral damage after 30 years of logging (Pinard and Cropper 2000; Pinard and Putz 1997). Based on carbon dynamic models in Dipterocarp forests, Pinard and Cropper (2000) reported that over 60 years following RIL, the average of total C stored in the forest was 36 Mg C ha$^{-1}$ higher than that CVL. Therefore, RIL is recommended as an appropriate technique for selective logging in the tropics (Elias et al. 2001; Sist, Garcia-Fernandez, and Fredericksen 2008).

Logging in Bornean lowland forests will always be a routine activity due to at least two reasons. The first reason is that forestry industry sectors will always continue in order to fulfill timber demand that is increasing over time (ITTO 2015). As an example, timber consumption has increased from 271 million m$^3$ (2012) to 275 million m$^3$ (2014) worldwide. The second reason is that forestry industry sectors are a significant source of income to the developing countries (Berry et al. 2010; Miles and Kapos 2008) such as Indonesia (approx. 2.6 billion USD) and Malaysia (3.7 billion USD) that produce approx. 41% of roundwood of the world timber market (FAO 2016). However, the contribution benefits to the income of the countries grew slower (Lebedys and Li 2014) and logged forests are under pressure for conversion to other more profitable land uses such as palm oil plantation and agricultural use (Sodhi et al. 2004).

## 1.6. Study objective, research question, and hypothesis

The main objective of this study is to assess the long-term effect of logging on the five main C. The specific objectives of the study were to:

a. Estimate the variability of C stocks, particularly above-, below-ground biomass, deadwood, and litter stocks, after different time since logging in a certified concessionaire in Berau, East Kalimantan (Chapter 2),
b. Compare method efficiency of deadwood estimation using fixed area sampling (FAS) and line-intersect sampling (LIS) methods simultaneously with the use of wood decay classification (3 classes) and dynamic penetrometer to estimate each specific deadwood density (Chapter 2),

c. Estimate the variability of total C stocks and evaluate the main driver influencing each C pool and total C stocks under different logging intensities in Malinau 16 years after logging (Chapter 3 and 4)

The results of this study aim to contribute and to understand the long-term influence of logging intensity on the major five C pools, which may not only increase the understanding of unstudied Indonesian logged forests especially on ecosystem C budget in a long-term period but also to serve as a practical guide for sustainable forest management and provide precise estimation that could be used as a benchmark value for total C stocks in Indonesian logged forests.

Toward that objective, the underlying motivation of this thesis based on the considerations discussed above is to answer the main question: *to what extent does logging (i.e. logging intensity) affect each C pool and total C stocks in Dipterocarp forest of Borneo.* Specifically, this study addresses specific research questions as follows:

Chapter 2. Estimating the variability of C stocks (AGC, BGC, deadwood, and litter) under different time since logging and comparing method efficiency for deadwood stocks estimation in Berau (East Kalimantan).

a. What is the variability of C stocks in logged forests under different time since logging?
b. Do LIS and FAS serve equally to predict deadwood stocks in logged forests?
c. What is the minimum sampling unit to accurately estimate deadwood stocks in logged forests?

Chapter 3. Estimating the variability of C stocks (AGC, BGC, deadwood, litter, and SOC) under different of logging intensities and disentangling the driver of C stocks in the logged forest in MRF.

a. What are the variability and the proportion of C stocks in logged forests under different logging intensities?
b. What are the main drivers affecting C stocks in MRF?
c. How does logging intensity influence each C pool and total C stocks?

Chapter 4. Evaluating the main driver influencing SOC stocks for each layer and each accumulation layer in MRF.

a. What are the variability and the main driver influencing SOC stocks in each layer and each accumulated layer?
b. How do logging intensities influence SOC stocks in each layer and each accumulated layer?

Based on the main research question, we expect that AGC and BGC are negatively affected by logging intensity; and deadwood is positively affected by logging intensity. Due to the high proportion of C stored in living trees (AGC and BGC), we expect that total C stock is also negatively affected by logging intensity. Therefore, the main hypothesis of this study is that logging still has an influence and still play crucial role on total C stocks 16 years after logging. The specific hypothesis is that the higher logging intensity the less C stocks in the forests. A hypothesized on the effects of logging intensity along time on total C stocks and the dynamic of each C pool following logging is presented in Figure 1-1.

## 1.7. Thesis outline

This thesis is a paper-based publication thesis with each chapter (2, 3, and 4) already published or to be published in peer-review scientific journals. Even though as a compilation of scientific papers, all chapters are within the same topic i.e. C stocks in Dipterocarp logged forest of Borneo (Figure 1-4), starting with a general overview and ending with conclusions. The introduction (**Chapter 1**) consists of (1) context and challenges including literature background about C stocks and each carbon pool in tropical forests particularly in logged forests, (2) state of the art of this thesis including objective, research questions, and the hypothesis of the study, and (3) the general overview of Bornean forests. **Chapter 2** consists of C stocks estimation (AGC, BGC, deadwood, and litter) under different time since logging condition (manuscript) with a focus on deadwood measurements methodology (will be submitted to *Forest Ecosystems*). **Chapter 3** consists of carbon stocks estimation (AGC, BGC, deadwood, litter, and SOC) and detecting logging imprint using linear mixed models in MRF (published in *Forest Ecology and Management*). **Chapter 4** consists of an assessment of logging intensity on SOC stocks 16 years after logging (will be submitted to *Plant and Soil*). The two final chapters (**Chapter 5** and **6**) discuss and present the main findings as well as the future possible investigations to be carried out in the issue of the impact of logging on C stocks in tropical production forests.

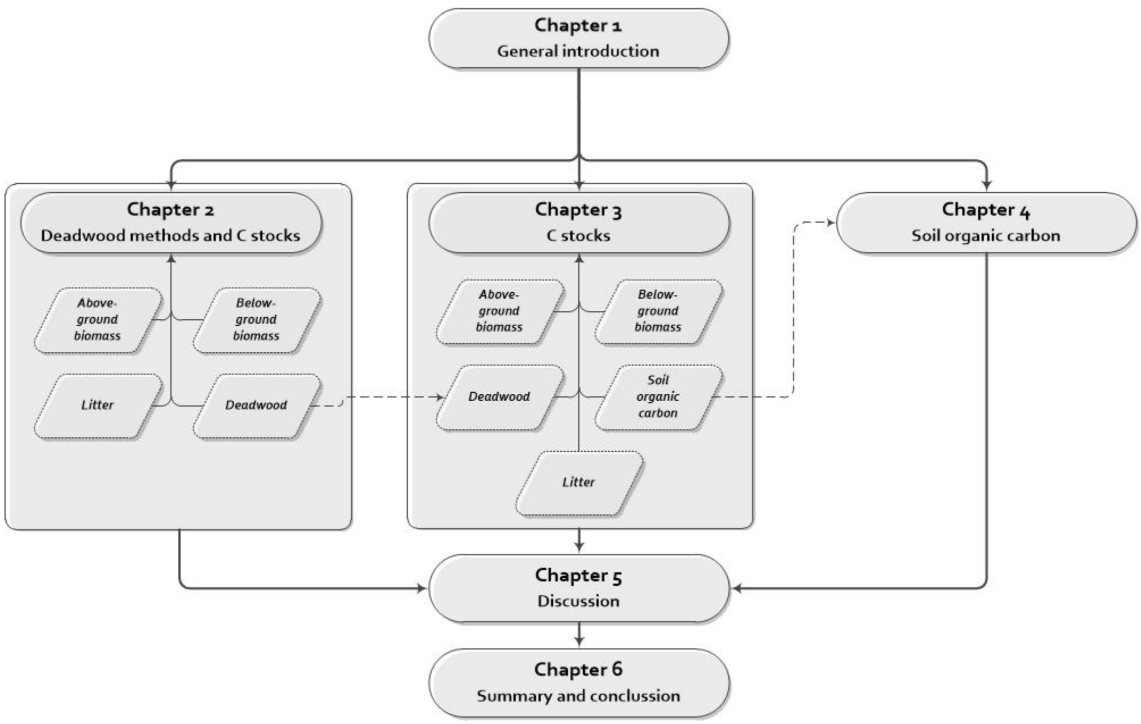

*Figure 1-4 Thesis structure and connections between chapters.*

# 2

# How do we estimate deadwood stocks in disturbed forests? A carbon stocks assessment study in Bornean logged forests

*Measuring specific density of fallen deadwood using a dynamic penetrometer in a Dipterocarp forest (Berau, East Kalimantan)*

*(Picture by Andes Hamuraby Rozak)*

# Abstract

*Background*: The variability and amount of carbon (C) stocks in tropical forests remain largely understudied, especially in logged forests where deadwood can form a significant fraction of total carbon stocks. However, only few studies have been conducted regarding deadwood stocks in Bornean logged forests. The goals of this study are to provide a guidance to efficiently estimate deadwood stocks in logged tropical forests and to get a refine estimation of total C stocks in the different time since logging.

*Methods*: Deadwood stock is assessed using fixed-area (FAS) and line-intersect (LIS) sampling methods along with two ways of assessing specific deadwood density (i.e. visual decay classification and dynamic penetrometer). Both methods were then compared in term of stocks, bias, sampling variance, and sampling efficiency. Further, tree biomass (i.e. above- and below-ground biomass) were estimated using allometric equations. Litter was estimated based on fixed-area method. Total C stocks in the forests were then estimated as the sum of tree biomass, deadwood, and litter stocks.

*Results*: FAS was more efficient and faster to estimate deadwood compared to LIS, with differences ranging between 17 and 23%. Visual classification greatly reduced the effort (*c.* 25-30% faster than using a penetrometer), without significant difference in deadwood estimates between both methods. Further, using a FAS and decay class method, total C stocks in our sites ranged from 130.2 to 173.7 Mg C $ha^{-1}$ where the recently logged site (logged in 2010) has significantly lower total C stocks compared to the forest that logged in 2007 and 2003. The main driver of C stocks was tree biomass where it forms 83% of C followed by deadwood (15%) and litter (2%).

*Conclusions*: Our study provides a first step towards accurate and efficient methods to quantify deadwood stocks in degraded tropical forests. Further, our result also refines an estimation of total C stocks in the different time since logging. These results promote a better understanding on the impact of logging on C balance in the tropics with the emphasize to deadwood stocks.

**Keywords**

Coarse woody debris; C stocks, logged tropical forests; sampling methods; penetrometer; wood decay, deadwood, Dipterocarp forests

## 2.1 Introduction

Deadwood plays crucial ecological functions in forest ecosystems, providing habitat and food for myriads of organisms (Harmon et al. 1986) and forming an essential step in nutrient cycling (Chambers, Schimel, and Nobre 2001). In tropical forests, deadwood stocks vary both spatially and temporally, with a range of 0.3 up to 83.7 Mg C $ha^{-1}$, due to differences in forest dynamics (Chao et al. 2009), disturbance regimes (Harmon et al. 1995; Osone et al. 2016; Pfeifer et al. 2015) and environmental factors controlling wood decay (Garbarino et al. 2015; Hérault et al. 2010; Weedon et al. 2009). While in old-growth forests deadwood can form up to 20% of total above-ground carbon, this ratio can rise up to 50% in heavily logged forests (Pfeifer et al. 2015). In 2010, half of the remaining Bornean forests were considered as logged (Gaveau et al. 2014), likely to temporally shift the distribution of above-ground carbon pools from live biomass to deadwood. Efficient methods to accurately estimate deadwood stocks in logged forests are therefore needed.

Several methods have been developed to estimate deadwood stocks in forest ecosystems. Among these, line-intersect sampling (hereafter LIS) (Van Wagner 1982; Van Wagner 1968; Warren and Olsen 1964), and fixed area sampling (hereafter FAS) (Harmon and Sexton 1996) have been widely applied (Russell et al. 2015). While some new methods (Gove et al. 2001; Ståhl 1998) have been developed in temperate forests, LIS and FAS remain popular for forest deadwood inventories (Russell et al. 2015; Woodall et al. 2009). Practically, LIS is a probability-proportional-to-length sampling method and consist of one or more transect lines along which all intersecting down deadwood above a given diameter are measured (Van Wagner 1968; Warren and Olsen 1964). FAS is based on the frequency of occurrence of individual deadwood within a given area where the length and diameter at both extremities of each deadwood lying within the sample unit are measured (Gove and Deusen 2011). Thus, FAS enables both fallen and standing deadwood to be assessed, while LIS account only for fallen deadwood (Harmon and Sexton 1996). Therefore, some studies combine LIS and FAS to estimate both fallen and standing deadwood (Carlson et al. 2016; Ngo et al. 2013). Although both methods have been applied in natural and logged tropical forests (Gerwing 2002; Keller et al. 2004; Palace et al. 2007), to our knowledge, no comparison of efficiency and accuracy of both methods in estimating deadwood stocks in logged tropical forests has been carried out.

The present study provides a first comparison of both LIS and FAS methods ability to capture deadwood stocks in Bornean logged Dipterocarp forests, simultaneously testing two ways of assessing deadwood density through visual classification ($FAS_{vis}$ and $LIS_{vis}$) and dynamic penetrometer ($FAS_{pen}$ and $LIS_{pen}$). The use of direct measurement using a dynamic penetrometer was reported to return more precise estimation of deadwood mass compared to visual classification, but at higher time cost (Larjavaara and Muller-Landau 2010). Integrating the result of deadwood assessment, total C stocks (including tree biomass and litter) were also estimated within the study area. Indeed, commercial logging directly reduces AGC through the direct harvest of large trees and killing/smashing on non-target trees and this pool has been largely understudied (e.g. Pinard and Putz 1996; Blanc et al. 2009; Sist et al. 2014; Rutishauser et al. 2015). However, a better understanding of the proportion and variability of C pools is needed to accurately estimate the C footprint due to logging (Saner et al. 2012; Rozak et al. 2018). Therefore, the aims of the study were (1) to evaluate the methodology for deadwood stocks measurement, and (2) to estimate the variability of total C stocks in logged forests. Specifically, the following questions were addressed: (1) what is the variability of deadwood estimated by LIS and FAS, (2) does LIS and FAS serve equally to predict fallen deadwood stocks, and (3) what is the variability and total C stocks in these forests. With regards to deadwood method comparison, we were stressed to compare fallen deadwood stocks as LIS only consider fallen deadwood. The goals of this study are to provide practitioners with enlightened guidance to efficiently estimate deadwood stocks in logged tropical forests and to get a refine estimation of total C stocks in the different time since logging.

## 2.2 Materials and methods

### 2.2.1 Study site

This study was carried out in a certified forest concession managed by PT Hutansanggam Labanan Lestari (HLL) in Berau District, East Kalimantan, Indonesian Borneo (Figure 2-1). Forests are described as 'Dipterocarp lowland tropical rainforest', dominated by Dipterocarpaceae species, such as *Hopea* spp., *Shorea* spp., and *Dipterocarpus* spp. encompassing most commercial species harvested in the concessionaire (Arbainsyah et al. 2014). The slope at our site ranged from 0-30% and consists of a rolling hilly landscape with a maximum elevation of 140 m above sea level. The average temperature is ranged between 21-33 °C with annual rainfall 1,500 – 3,000 mm. Reduced-impact Logging (RIL) techniques and medium harvest intensity (6-8 trees $ha^{-1}$) were applied across the study sites.

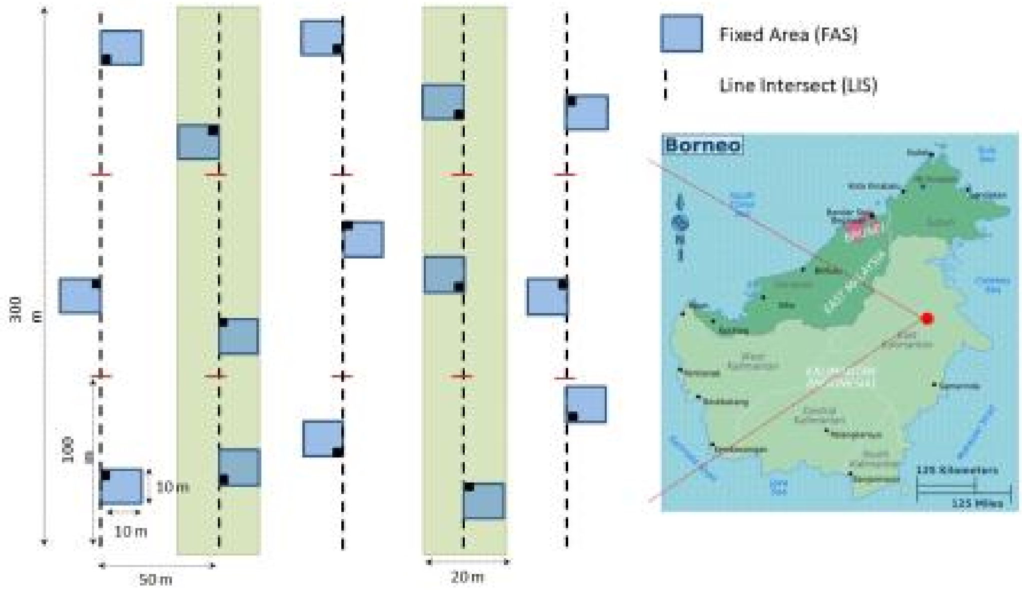


*Figure 2-1 Map of study sites in Berau, East Kalimantan and sampling design set up at each of the 3 sites sampled: For LIS, dashed lines show 300-m transect lines located 50 m apart of each other; FAS are illustrated with blue squares (10 m x 10 m each) randomly placed along the transect lines in each 100-m section. Each 300-m line transect and a set of 3 FAS is considered as an independent sampling unit, resulting in 5 sampling units by site. Green areas (20 m x 300 m each) were used for tree inventory. Black squares (1 m x 1 m each) within FAS were used for litter sampling.*

### 2.2.2 Study design

Our sampling design was inherited from a previous study investigating the interplay between logging and species diversity (Arbainsyah et al. 2014). Owing the difficulty to access a logging concession with known logging history, we have taken advantage of the pre-existing transects set up by that previous study. Three study sites (hereafter site) were originally selected based on time since logging: 12 (2003), 8 (2007), and 5 (2010) years after logging (thereinafter y.a.l.). Each site covers an area of 300 m x 200 m with a 10-m buffer zone on both sides, equivalent to the width of a FAS subplot, totaling 6.6 ha per site. At each site, five parallel transect lines, located 50 m apart, were set up and divided into 100-m sections (Figure 2-1). Each 300-m transect line was considered as an independent sampling unit for LIS along which the diameter of all deadwood ≥10 cm intersecting the transect line was measured. A FAS sample unit consisted of 3 quadrats of 10 m x 10 m randomly located on either side of each transect line, i.e. one quadrat per 100-m section of the LIS transect. All fallen and standing deadwoods with a diameter ≥10 cm laying in a given FAS quadrat were measured. For fallen deadwood, we followed the "chainsaw protocol" (Gove and Deusen 2011), where all fallen deadwoods that cross or lye in the quadrat are measured. For logs expanding outside the quadrat's limits, extremities refer to points intersecting any boundary. Diameters are measured at each extremity along with the distance between both extremities. For standing deadwood, diameter at 130 cm (DBH) and height (using a laser rangefinder or tape measure whenever possible) were recorded. Most fallen and standing deadwood were measured with a standard diameter tape. For a few large deadwood or very decayed pieces, two metallic rulers were placed on both side of the pieces and the vertical distance from the ground to the upper part of a given piece and the horizontal distance between the two rulers were measured. Assuming that all pieces were circular is likely to overestimate the actual volume (Fraver, Ringvall, and Jonsson 2007), but the problem would likely affect FAS and LIS to a same degree.

To avoid large spatial heterogeneity, deadwood stocks estimated in FAS quadrats were averaged by transect. We tested for spatial autocorrelation within FAS and LIS sample units but found no significant correlation (Figure 2-6). This result excludes any possibility of pseudoreplication. Additionally, no significant difference was found among sites (Figure 2-7), and therefore we have decided to lump all fifteen sampling units in both methods.

The time spent in installing each sampling unit and searching/measuring deadwood (for LIS and FAS) were systematically recorded to assess the effort needed and ultimately compare methods' efficiency (E). For FAS, we estimated the time to walk from one quadrat to the other as the distance between the starting point of each transect to the farthest quadrat covered at a 2.5 km hour$^{-1}$ equivalent to the average walking speed of the field crew composed of 3 people which was 30% faster than walking time used in sampling efficacy analysis in tropical China (Hou et al. 2015). We acknowledge that walking along a pre-installed transect line may slightly underestimate installation time in FAS. Topography at our site ranged from 0 to 30%, leading to a maximal difference in projected length/area of 4% for a given sampling unit (Brown 1974). This error is in the range of measurement error and no particular slope correction was applied.

Two transect areas i.e. the area of 20 m along the two transect lines were used for tree inventory (Figure 2-1, green area), totaling 1.2 ha for each site. Live trees with a DBH ≥10 cm or 50 cm above any buttress or deformity within the area were measured and identified by parabotanist to the lowest taxonomic levels. A total of 1,545 were identified at species (60%), and genus (40%). While, a total of 15 subplots (1 m x 1 m, black squares,Figure 2-1) in each site was used to estimate litter mass.

### 2.2.3 Volume and mass estimation of deadwood

In LIS, the basic technique involves measuring the diameter of any fallen deadwood perpendicularly to its central axis at the point of intersection with the transect line (Van Wagner 1982; Van Wagner 1968). The formula used to calculate the volume per surface area of fallen deadwood ($V_{LIS}$, m$^3$ ha$^{-1}$) is:

$$V_{LIS} = \frac{\pi^2}{8 * L_t} * \sum d^2$$

, where $L_t$ the transect length (m) and $d$ the diameter (cm) of any piece of woody debris intersecting the transect line. Deadwood mass (Mg ha$^{-1}$) was estimated by multiplying $V_{LIS}$ by its respective specific deadwood density ($\rho$, g cm$^{-3}$) estimated either by visual classification ($LIS_{vis}$) or by penetrometer ($LIS_{pen}$).

In FAS, the volume of fallen deadwood per surface area ($V_{FAS}$, m$^3$ ha$^{-1}$) was estimated using a conic-paraboloid formula (Fraver, Ringvall, and Jonsson 2007) and divided by the area of sampling unit (300 m$^2$). The formula used to calculate the volume per surface area of fallen deadwood in FAS is:

$$V_{FAS} = \frac{L_d}{12} * \left(5 * A_s + 5 * A_l + 2 * \sqrt{A_s * A_l}\,\right) * \frac{1}{A_{SU}}$$

, where $L_d$ is the length of a deadwood (m), $A_s$ and $A_l$ are the cross-sectional area at the small- and large-end diameter of deadwood (m$^2$), and $A_{SU}$ is the area of sampling unit (ha), respectively. The volume of a standing deadwood was considered as cylinders ($V_s = \pi \cdot r^2 \cdot h$) to which a generic form factor of 0.48 was applied (Cannell 1984).

Deadwood masses for fallen and standing deadwood for each sampling unit were estimated by multiplying $V_{FAS}$ by its specific deadwood density estimated either by visual classification for fallen ($FAS_{vis}$) and standing deadwood ($S_{vis}$) or by penetrometer for fallen ($FAS_{pen}$) and standing deadwood ($S_{pen}$). Each deadwood mass (Mg ha$^{-1}$) predicted by LIS and FAS was then converted to deadwood carbon stock (Mg C ha$^{-1}$).

### 2.2.4 Deadwood specific density

Deadwood density is generally assessed through a visual classification of wood decay. Here, we followed the classification of Walker et al. (2014):

Class 1 (Solid): extensive bark cover, leaves and fine twigs still present, logs relatively undecayed.

Class 2 (Intermediate): No bark and few branch stubs (not moving when pulled), sapwood decaying

Class 3 (Rotten): Wood often scattered across the soil surface, logs elliptical in cross-section.

For each class, average dry wood density was determined in collecting 13, 17, and 25 of wood samples for class 1, 2, and 3, respectively. Wood samples were weighed fresh and oven-dried (at 80 °C until constant weight) to compute dry weight per fresh/wet volume. As we were unable to differentiate logging residuals from incidental or natural mortality, wood densities are assumed to represent the surrounding forest as a whole.

For each deadwood piece, decay was estimated through a dynamic penetrometer (in the center of the wood piece) and by visual classification (of the same section). For calibration of the penetrometer and decay classes, 55 cross-sections, where both measurements have been done, were randomly collected. The dynamic penetrometer utilizes a moving weight to apply a standardized amount of kinetic energy to penetrates the piece of woody debris. The number of hits and depth of penetration were recorded to derive a penetration index (*X,* mm hit$^{-1}$), i.e. the ratio between the depth of penetration and number of hits. A function relating this index and wood density was calibrated on the same wood samples used for the decay classification. Results on wood density analysis are presented in the supplementary information.

### 2.2.5 Tree biomass estimation

Above-ground biomass (AGB, kg) of each tree was estimated using a recent generic allometric model (Chave et al. 2014) incorporating a measure of environmental strees ES, a specific wood tree density ρ (g cm$^{-3}$), and a diameter at breast height DBH (cm). The equation as follows:

$$AGB = \exp[-1.803 - 0.976 * ES + 0.976 * \ln(\rho) + 2.673 * \ln(DBH) - 0.0299 * [\ln(DBH)]^2]$$

Even though there are local allometric models developed in Dipterocarp forests (Basuki et al. 2009; Kenzo et al. 2009), such generic model was found more accurate than local models (Rutishauser et al. 2013). Wood tree densities were extracted from the Global Wood Density Database (Chave et al. 2009; Zanne et al. 2009). Genus average wood density was used for tree identified until the genus level (Slik 2006).

Below-ground biomass (BGB, kg) of each tree was estimated using an allometric model including DBH developed in Dipterocarp forest (Niiyama et al. 2010). The equation as follows:

$$BGB = 0.023 * DBH^{2.59}$$

### 2.2.6 Litter stocks

Litter is defined as all dead organic material on top of the mineral soil including deadwood with diameter <10 cm (Walker et al. 2014). The litter sample was collected within subplot (Figure 3-1, black squares) and weighed wet. A sub-sample was then oven-dried at 80 °C until constant weight to estimate the dry weight. Litter dry mass was established based on the wet-to-dry ratio of sub-samples.

### 2.2.7 Data analysis

The first aim of the study was to analyze deadwood stock methodology. Deadwood stocks were averaged by sampling units and 95% confidence intervals (CI) were computed using 1000 bootstrap replicates. A paired student's t-test was performed to detect differences between FAS and LIS. As LIS doesn't allow standing deadwood to be estimated, comparisons are restricted to fallen deadwood.

The coefficient of variation of the sample (CV, %) was used as a normalized measure of dispersion of deadwood stocks:

$$CV = \frac{s}{\overline{x}} * 100$$

, where $s$ and $\overline{x}$ are, respectively, the standard deviation and the mean of fallen deadwood stocks computed among sampling units. The use of CV enabled deadwood stocks to be compared on a similar basis (Wagner et al. 2010). Therefore, we investigated how increasing sample size (i.e. increasing the number of sampling units) affected CVs. CV was computed for different sample sizes (1 to 15 sampling units) using a bootstrap procedure.

Method efficiency (E) was calculated as (Ducey et al. 2013; Jordan, Ducey, and Gove 2004):

$$E = \frac{\bar{t}_{FAS} * S^2{}_{FAS}}{\bar{t}_{LIS} * S^2{}_{LIS}}$$

, where $\bar{t}$ and $S^2$ are, respectively, the mean time required for installing and measuring deadwood per sampling unit and the variance among all sampling units (n = 15) of a given method. Due to the absence of true measures of deadwood stocks and workers should physically cross all deadwood along the transect line, LIS was used as the reference, as it also returned unbiased deadwood estimates except the conditions explained by Ringvall and Stahl (1999). Therefore, LIS would be considered as more efficient than FAS if E >1 (Jordan, Ducey, and Gove 2004). Root mean square error (RMSE), sampling variance ($S^2$), and $bias^2$ were also computed in order to compare both methods (Jordan, Ducey, and Gove 2004). RMSE was computed as:

$$RMSE = \sqrt{S^2 + bias^2}$$

where $bias^2$ for LIS assumed to be 0 and negative $bias^2$ for FAS assigned to be 0.

The minimal number of sampling units needed ($n_{req}$) to estimate mean deadwood stocks within an error *e* at an error rate ɣ was estimated using the following formula:

$$n_{req} = \frac{S^2 * t^2_{[ɣ,n-1]}}{e^2}$$

, where t is the Student's t-statistic (set to 1.96, the value from the normal distribution, to relax its dependence on the number of observation) and $S^2$ is the average sample variance. The number of sampling units needed was computed at 5, 10, 15, and 20% error rates. Effort (expressed as hours needed) required by each method was calculated by multiplying $n_{req}$ by the average time ($\bar{t}$) required to install and measure a sampling unit.

The second aim of the study was to estimate the total C stocks in the logged forests. Total C stock is defined as the sum of each C pool (i.e. AGC, BGC, deadwood, and litter) and presented as Mg C ha$^{-1}$. For sake of simplicity, the C content of each C pool (deadwood, AGB, BGB, and litter) was estimated using a default value of 47% (IPCC 2006). However, this default value, particularly deadwood, might slightly vary but is closer to the values reported in tropical lowland forests of Sumatra (Meriem et al. 2016). Analysis of variance (Anova) was performed to test the difference of each C pool among sites followed by TukeyHSD test. Significantly different was assigned when P <0.05. All analyses were performed in R language (R Core Team 2017).

## 2.3 Results

### 2.3.1 Deadwood stocks

Using a visual classification, fallen deadwood stocks averaged 21.4 (18.3 – 25.1) and 25.8 (22.2 – 28.9) Mg C ha$^{-1}$, for FAS and LIS respectively (Table 2-1). LIS estimates were on average 17.1% (visual classification) and 22.9% (penetrometer) higher than FAS ones, being significantly different (all $P$ <0.05). In FAS, standing deadwood was also assessed and formed only 3% (0.3 – 1.3 Mg C ha$^{-1}$) of total deadwood stocks. When comparing both wood density estimation methods, deadwood estimates were similar for FAS (total deadwood: 22.2 (19.2 – 25.7) vs 22.3 (19.8 – 25.6) Mg C ha$^{-1}$ for decay class and penetrometer, respectively) and LIS (Table 2-1, fallen deadwood: 25.8 (22.2 – 28.9) vs 27.9 (24.2 – 31.5) Mg C ha$^{-1}$ for decay class and penetrometer, respectively).

*Table 2-1 The average of fallen, standing, and total deadwood stocks (Mg C ha-1, 95% CI) estimated by LIS and FAS.*

| Variable | FAS | LIS | Average difference (%) | df | t-value | *P* |
|---|---|---|---|---|---|---|
| **Carbon mass predicted by decay class (Mg C ha$^{-1}$)** | | | | | | |
| **Fallen** | 21.4 (18.3 – 25.1) | 25.8 (22.2 – 28.9) | 17.1 | 14 | -2.7 | 0.02 |
| **Standing** | 0.7 (0.3 – 1.3) | - | - | na | na | na |
| **Total** | 22.2 (19.2 – 25.7) | - | - | na | na | na |
| **Carbon mass predicted by penetrometer (Mg C ha$^{-1}$)** | | | | | | |
| **Fallen** | 21.5 (18.7 – 25.0) | 27.9 (24.2 – 31.5) | 22.9 | 14 | -3.4 | <0.01 |
| **Standing** | 0.8 (0.3 – 1.4) | - | - | na | na | na |
| **Total** | 22.3 (19.8 – 25.6) | - | - | na | na | na |

### 2.3.2 Methods comparison for deadwood measurement

Interestingly, both methods did not capture deadwood variability similarly (Table 2-2, $S^2$). For instance, the variability of deadwood decreased with time since logging in FAS, whereas this was not the case for LIS. Variance estimated by LIS was relatively higher compared to FAS except in the most recently logged site (54.0 vs 116.1 and 74.4 vs 106.3 for LIS and FAS estimated by decay classification and penetrometer, respectively). However, when all sampling units were lumped together, both methods return relatively similar variance (Table 2-2, all sites). As the bias in LIS was null, the total error (RMSE) of FAS was systematically higher than LIS but did not greatly differ when all sites are considered (Table 2-2). The different ability to capture deadwood variability among both methods is further revealed by their respective CVs (Figure 2-2). Overall, six and eight sampling units are needed to estimate mean deadwood mass below 10% CV in a 6.6-ha study area for LIS and FAS, respectively.

*Table 2-2 Summary of sampling variance ($S^2$), bias ($Bias^2$), root mean square error (RMSE) and efficiency (E) for deadwood stocks (Mg C $ha^{-1}$) estimated by decay class and penetrometer for each site (n = 5) and all sites (n = 15). $Bias^2$ in LIS assumed to be zero and negative $bias^2$ assigned as zero (*).*

| Site | Decay class | | Penetrometer | |
|---|---|---|---|---|
| | LIS | FAS | LIS | FAS |
| $S^2$ | | | | |
| 12 y.a.l. | 8.0 | 3.4 | 4.1 | 3.9 |
| 8 y.a.l. | 93.6 | 15.8 | 115.4 | 6.3 |
| 5 y.a.l. | 54.0 | 116.1 | 74.4 | 106.3 |
| All sites | 46.7 | 44.8 | 55.8 | 41.1 |
| $Bias^2$ | | | | |
| 12 y.a.l. | 0 | 25.3 | 0 | 26.3 |
| 8 y.a.l. | 0 | 88.9 | 0 | 161.3 |
| 5 y.a.l. | 0 | 0* | 0 | 0* |
| All sites | 0 | 14.2 | 0 | 51.7 |
| RMSE | | | | |
| 12 y.a.l. | 2.8 | 5.4 | 2.0 | 5.5 |
| 8 y.a.l. | 9.7 | 10.2 | 10.7 | 12.9 |
| 5 y.a.l. | 7.3 | 10.8 | 8.6 | 10.3 |
| All sites | 6.8 | 7.7 | 7.5 | 9.6 |
| E | | | | |

| | | | | |
|---|---|---|---|---|
| 12 y.a.l. | - | 0.4 | - | 0.7 |
| 8 y.a.l. | - | 0.2 | - | 0.1 |
| 5 y.a.l. | - | 1.6 | - | 1.0 |
| All sites | - | 0.8 | - | 0.6 |

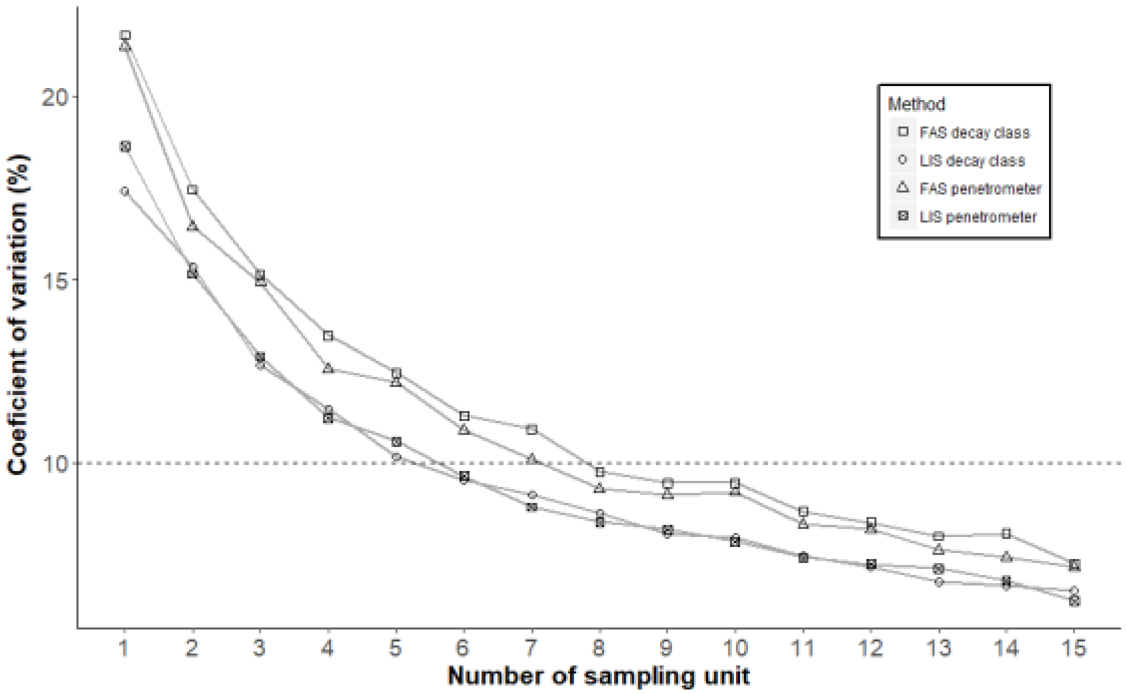


*Figure 2-2 The coefficient of variation (%) of mass by number of sampling unit estimated by FAS and LIS. Both masses estimated by FAS and LIS were simultaneously predicted using decay class and penetrometer. Each point represents 1000 simulations of each method. The horizontal dashed line shows an illustrated 10% coefficient of variation.*

The main difference between both methods lied in installation and measurement times (Table 2-3, Figure 2-8). Average time required per sampling unit for $FAS_{vis}$ and $LIS_{vis}$ was significantly different (Figure 2-8) with $FAS_{vis}$ being 14% faster than $LIS_{vis}$ (0.70 *vs* 0.81 hours, Table 3-3). As a consequence, $FAS_{vis}$ was found more efficient ($E$ = 0.8) than $LIS_{vis}$ to estimate deadwood across all three study sites (Table 2-2).

*Table 2-3 The average time of installation, measurement and total time required per sampling unit (hour, 95% CI) on predicting deadwood stocks using LIS and FAS methods. The average total time of FAS representing the average time required to install, measure, and walking of three subplots (100 $m^2$).*

| Method | Wood density estimation method | Average installation time (hour) | Average measurement time (hour) | Average total time (hour) |
|---|---|---|---|---|
| **FAS** | Decay class | 0.62 (0.58 – 0.65) | 0.05 (0.04 – 0.07) | 0.67 (0.63 – 0.71) |
| **LIS** | Decay class | 0.72 (0.69 – 0.76) | 0.09 (0.08 – 0.11) | 0.81 (0.78 – 0.84) |
| **FAS** | Penetrometer | 0.62 (0.58 – 0.65) | 0.27 (0.21 – 0.35) | 0.88 (0.80 – 1.00) |
| **LIS** | Penetrometer | 0.72 (0.69 – 0.76) | 0.46 (0.40 – 0.52) | 1.18 (1.12 – 1.24) |

## 2.3.3 Number of sampling units and effort needed to efficiently estimate deadwood

For $FAS_{vis}$, 13 and 4 sampling units of 300-$m^2$ per ha (equivalent to 39% and 12% of total area) are needed to estimate the average of total deadwood stocks with an error of 5 and 10%, respectively (Table 2-4). For $LIS_{vis}$, similar precision is attained with 12 and 3 sampling units of 300-m transects. In term of effort, $LIS_{vis}$ required more effort than $FAS_{vis}$ for the same level of error. For example, to estimate fallen deadwood with 10% error, 3.2 hours are needed by $LIS_{vis}$ compared to 2.8 hours by $FAS_{vis}$.

*Table 2-4 The number of sampling unit required (n) and respective effort needed (hours) to estimate mean fallen deadwood mass with N percent error (%) around the mean using FAS and LIS with a visual decay classification.*

| **Total FAS-plot size ($m^2$)** | | | **300** | |
|---|---|---|---|---|
| **Error (%)** | 5 | 10 | 15 | 20 |
| **n** | 13 | 4 | 2 | 1 |
| **Effort (hour)** | 8.7 | 2.7 | 1.3 | 0.7 |
| **Total LIS-transect length (m)** | | | **300** | |
| **Error (%)** | 5 | 10 | 15 | 20 |
| **n** | 12 | 3 | 2 | 1 |
| **Effort (hour)** | 9.7 | 3.2 | 1.6 | 0.8 |

## 2.3.4 Above-ground carbon stocks

Site 12 y.a.l. has significantly higher AGC compared to site 5 y.a.l. even though there was no significantly different of tree density among sites (Table 2-5). AGC reached 121 (95-146), 100 (78-124), and 81 (68-96) Mg C $ha^{-1}$ in site 12 y.a.l., 8 y.a.l., and 5 y.a.l., respectively. Large trees (DBH >60 cm) represented 2-3% of tree density but contained 27-31% of AGC. Small trees (DBH 10-30 cm) represented 81-82% of tree density but contained a small amount of AGC (22-28%). While medium trees (DBH 30-60 cm) represented in average 16% of tree density but gathered 35-47% of AGC.

*Table 2-5 The average tree density ($ha^{-1}$) and above-ground carbon stocks (AGC, Mg C $ha^{-1}$) in each site. Values in parentheses indicate 95% CI.*

| **Tree size class** | **Tree density** | | | **AGC** | | |
|---|---|---|---|---|---|---|
| | Site 12 y.a.l. | Site 8 y.a.l. | Site 5 y.a.l. | Site 12 y.a.l. | Site 8 y.a.l. | Site 5 y.a.l. |
| **DBH 10-30** | 343 (315-368) | 374 (311-434) | 327 (283-373) | 27 (24-30) | 26 (21-32) | 23 (19-26) |
| **DBH 30-60** | 69 (49-88) | 73 (52-96) | 64 (48-79) | 57 (41-74) | 47 (31-63) | 34 (24-43) |
| **DBH >60** | 13 (9-17) | 10 (5-16) | 12 (9-17) | 36 (24-50) | 27 (12-43) | 25 (17-33) |
| **Total** | 425 (277-578) | 456 (289-630) | 403 (263-558) | 121 (95-146) | 100 (78-124) | 81 (68-96) |

After decreasing size according to the respective AGC, ten species contributed for about half of the total AGC in each site (Figure 2-3, a list of all species can be found in supplementary material Table 2-9). *Shorea parvifolia* (Dipterocarpaceae) contributed approx. 7 and 13% to total AGC in site 12 y.a.l.and 5 y.a.l., respectively. While *Heritiera simplicifolia* (Malvaceae) contributed approx. 8% to total AGC in site 8 y.a.l. Dipterocarpaceae, the dominant tree family in our site, gathered a large portion of AGC (Figure 2-4, a list of all families can be found in supplementary material Table 2-10). Dipterocarpaceae contributed 38, 40, and 26% to total AGC in site 12 y.a.l., 8 y.a.l., and 5 y.a.l., respectively.

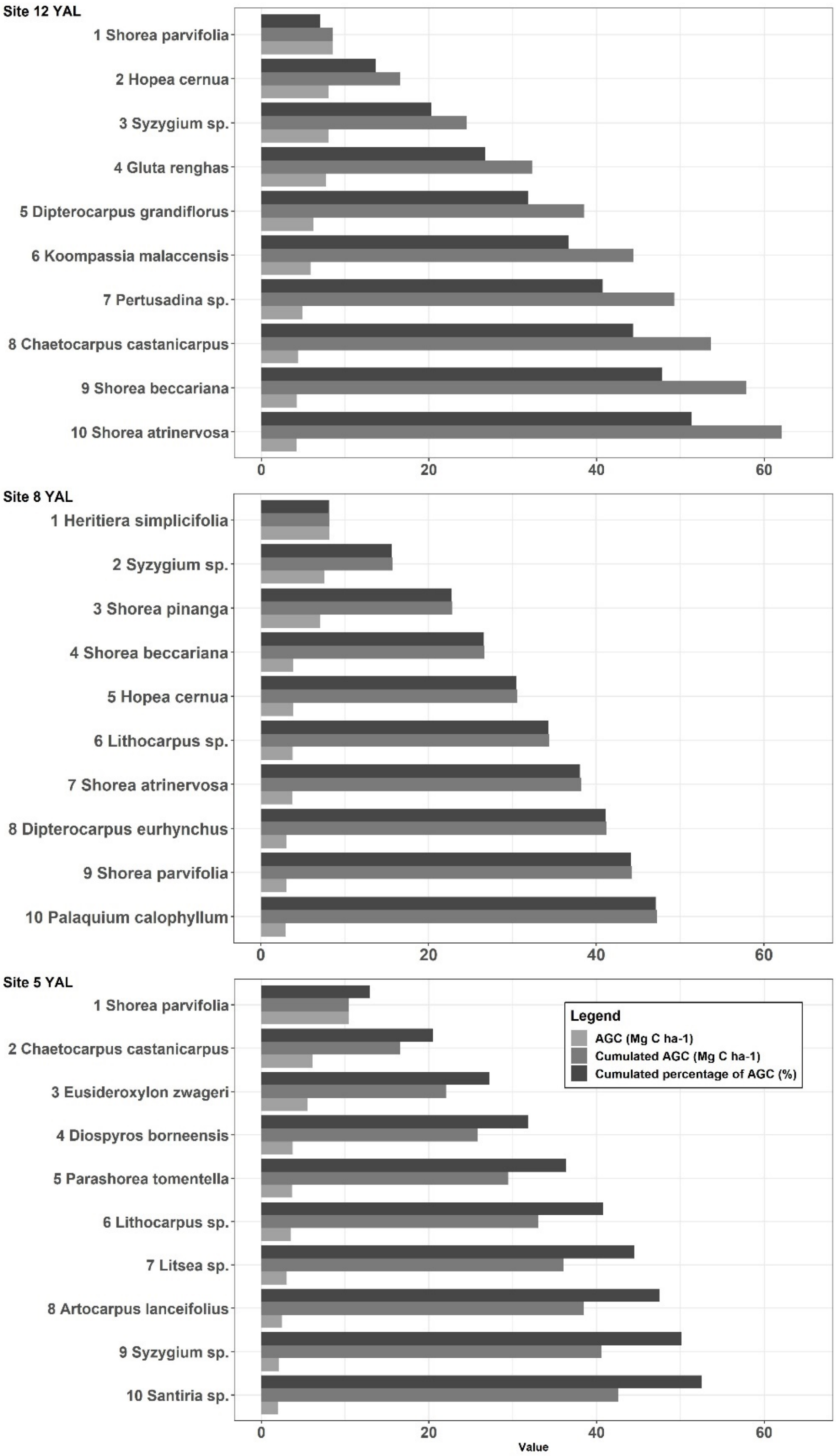


*Figure 2-3 Above-ground carbon (AGC, Mg C ha$^{-1}$), cumulated AGC (Mg C ha$^{-1}$), and cumulated percentage to total AGC (%) of 10 species in each site.*

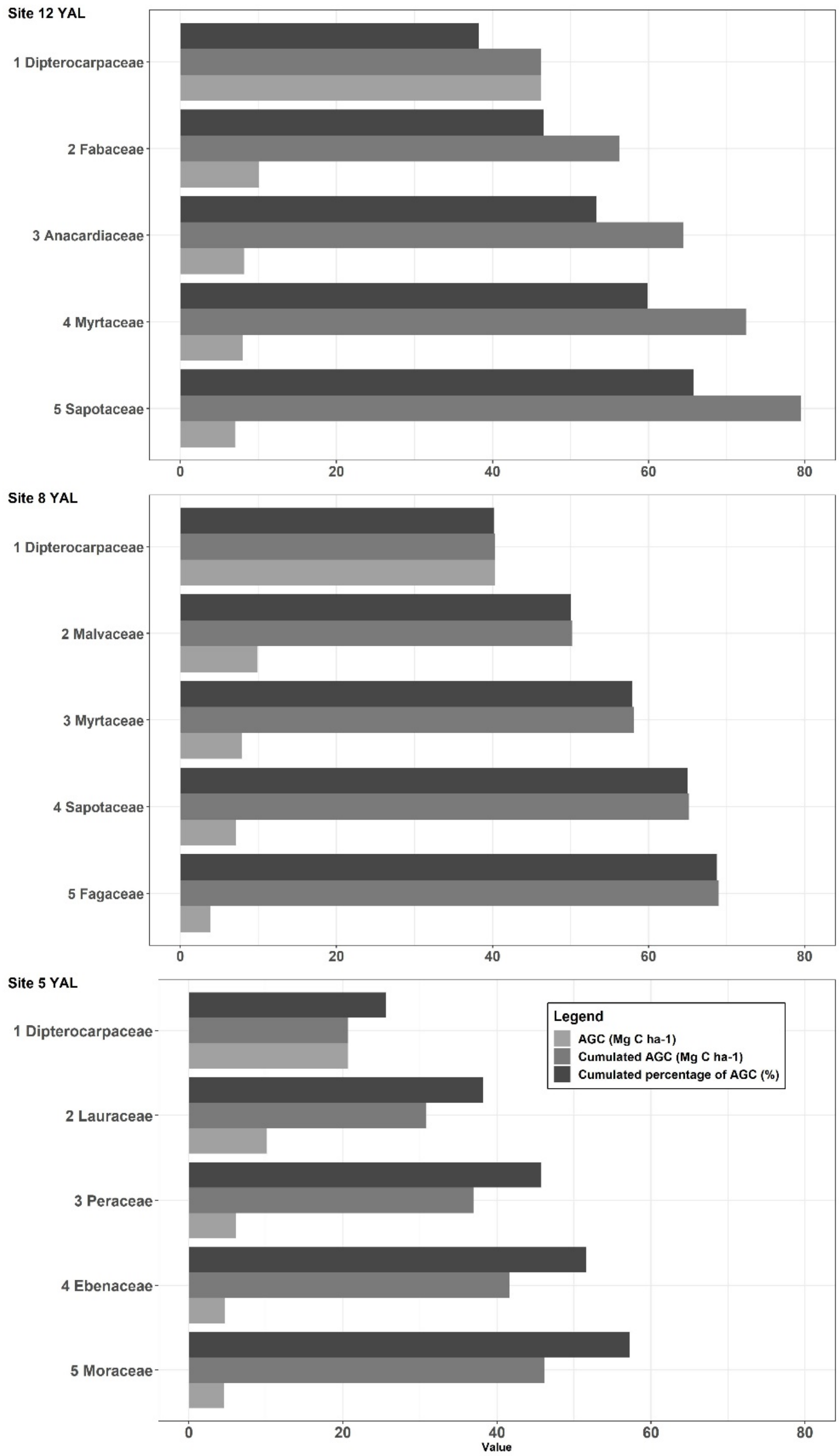


*Figure 2-4 Above-ground carbon (AGC, Mg C ha$^{-1}$), cumulated AGC (Mg C ha$^{-1}$), and cumulated percentage to total AGC (%) of 5 families in each site.*

## 2.3.5 C stocks estimations

Using a FAS and decay class method for measuring deadwood stocks, total C stocks varied among sites (Figure 2-5). Total C stocks in our study site ranged from 130.2 to 173.7 Mg C $ha^{-1}$ with an average of 151.1 Mg C $ha^{-1}$ (Figure 2-5A), where approx. 83% of C were found in tree biomass and followed by deadwood stocks (Figure 2-5B). Litter formed only a minor fraction of total C (approx. 2%). No significantly different were found for deadwood and litter stocks among sites (all $P$ >0.05). Forest logged in 2003 (12 y.a.l.) has significantly higher total C stocks compared to site 2007 (8 y.a.l.) and 2010 (5 y.a.l.).

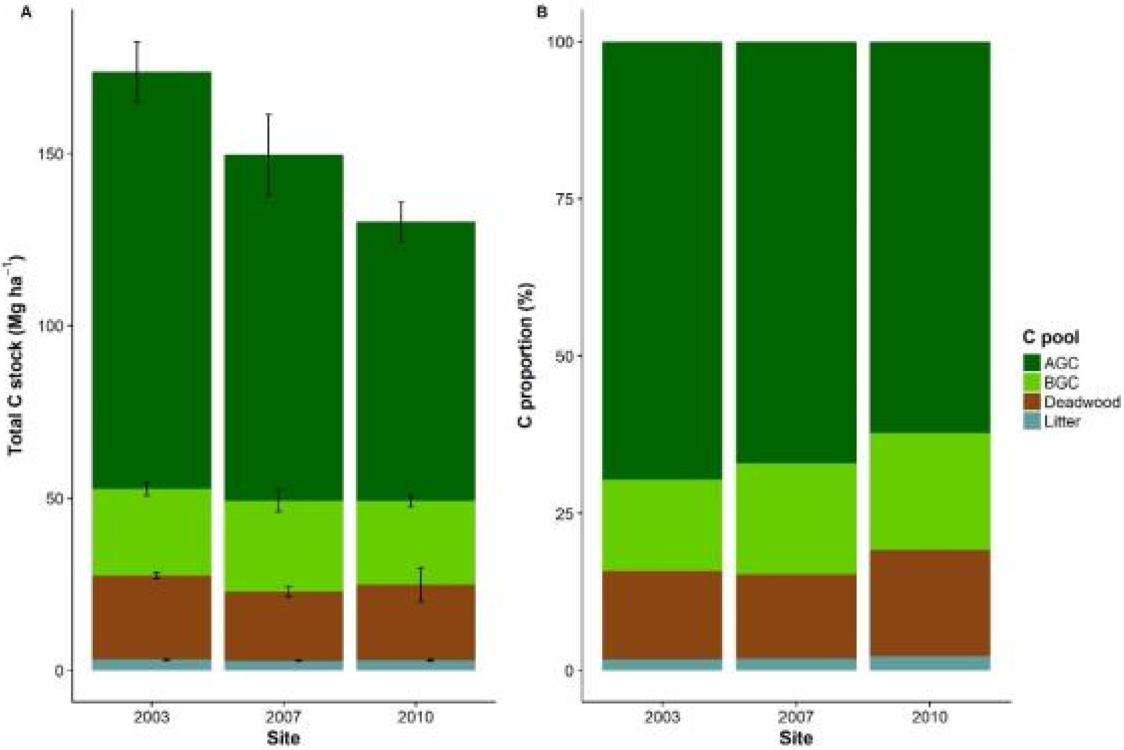


*Figure 2-5 Total C stocks (A) and proportion of C (B) for each pool among sites. Error bars indicate one standard error of the mean.*

## 2.4 Discussion

### 2.4.1 Methodological considerations to assess deadwood stocks in logged forests

Our study simultaneously aimed to compare two commonly-used methods i.e. FAS and LIS (using visual classification and penetrometer) to estimate deadwood carbon stocks and to estimate total C stocks in logged Dipterocarp forests. The efficiency of both methods has been largely discussed in the literature, mostly in temperate forests (Jordan, Ducey, and Gove 2004; Meo et al. 2017; Ritter and Saborowski 2014; Ritter and Saborowski 2012). Whereas both methods were reported to have relatively low CVs (typically <10%, Ritter and Saborowski (2014; 2012)), FAS involved higher effort (time) to obtain similar accuracy in deadwood estimates and the authors were to conclude that LIS was generally more efficient. Besides efficiency, LIS has also been recommended in forests with a large amount of deadwood (McKenzie et al. 2000; Woldendorp et al. 2004). In contrast, in forests with low and heterogeneous or clumped deadwood stocks, FAS might be more appropriate (Woldendorp et al. 2004) and our results are corroborating this statement because variability decreased with time since logging in FAS (Table 2-2).

Our study offers to test two commonly used sampling methods along with two different estimations of deadwood decay. Fallen deadwood stocks estimated by LIS were in average 17 and 23% higher than $FAS_{vis}$ and $FAS_{pen}$, respectively (Table 2-1). These differences are of the same magnitude than that reported in other studies (Baker et al. 2007; Warren, Keeton, and Kraft 2008). While LIS returns unbiased estimated of deadwood (unless some conditions explained by Ringvall and Stahl (1999), FAS stained with several sources of bias. One lies in of the "non-detection" errors, where the number of deadwood pieces increases with time of search (Jordan, Ducey, and Gove 2004). Here, the non-detection error is likely to be small due to the small size of the quadrats (100 $m^2$). Another source of bias lies in the estimation of deadwoods' volume in FAS which is of unknown magnitude when applied to any particular population of deadwood. Both issues are likely to explain the differences observed among both methods.

Generally, using a simple classification to estimate deadwood decay proved to return similar deadwood estimates (Table 2-1), but at a lower time cost (Table 2-3). Our results point toward the relative efficiency and reliability of a visual classification calibrated locally. In term of sampling methods, $FAS_{vis}$ was found more efficient than $LIS_{vis}$ across all three sites (E = 0.8, Table 2-2). However, in the recently-logged (5 y.a.l.) site, where the variance of deadwood stocks was high in $FAS_{vis}$ (Table 2-2), $LIS_{vis}$ was found more efficient (E = 1.6). Despite no significant difference in deadwood stocks among sites (Figure 3-7), the variance of deadwood differed with time since logging (Table 2-2). Increased variance in FAS in recently logged forests may suggest that FAS might be impacted by a clumped pattern of logging damage or waste, whereas LIS is not. Another advantage of FAS is that standing dead trees can also be assessed. While standing necromass was very low (3%) at our sites (Table 2-1), the sample time could increase in forests with a higher fraction of standing dead trees. Forest type and disturbance history are generally the controlling factors that determine the amount of deadwood, and no one “fit-them-all” method exists. As an example, recent protocols to measure carbon stocks in tropical rain forests (Marthews et al. 2012; Walker et al. 2014) recommend combining FAS (for standing deadwood) and LIS (for fallen deadwood).

More generally, our sampling design was inherited from a previous study (Arbainsyah et al. 2014) and hold some limitations. For instance, LIS assume that deadwood intersects the transect line at random what is only guaranteed if the transects are placed randomly (Kaiser 1983). Using parallel transects may have introduced a bias and some studies have investigated the optimal arrangement of transect lines to be used for deadwood measurement (Bell et al. 1996; Gregoire and Valentine 2003; Hazard and Pickford 1986). As both incidental damages (Iskandar et al. 2006; Sist and Nguyen-Thé 2002) and the percentage of ground area disturbed (Jackson, Fredericksen, and Malcolm 2002; Pearson, Brown, and Casarim 2014) largely vary on a per harvested tree basis, accurately sample such large heterogeneity at concessions scale (e.g. hundreds of hectare) remains challenging. For instance, small-scale aggregation of logging residuals may explain larger confidence intervals in recently logged forests.

### 2.4.2 Minimal sample size and effort to estimate deadwood

The number of sampling units and effort needed to estimate average deadwood stocks differed between FAS and LIS (Table 2-4). Despite greater total error and bias on a per sampling unit basis (Table 2-2), FAS required less effort than LIS to estimate average deadwood stocks with a given error (Table 2-4). Yet, some cautions should be taken to ensure that the sampling design efficiently captures the heterogeneity of logging by either randomly placing the sampling units across the whole plot area, or in applying a more efficient stratified sampling strategy. As dead standing trees are generally surveyed in permanent study plots (Chao et al. 2009), LIS is a popular method to rapidly monitor fallen deadwood (Ringvall and Stahl 1999). The effort of assessing standing deadwood solely by FAS was not carried out in the present study, but as FAS enables both standing and fallen components to be assessed, this technique is generally preferred for detailed forest carbon inventories. Combining FAS (for standing deadwood) and LIS (for fallen deadwood) might be another option in the forest with a high amount of standing dead trees. Unfortunately, this option could not be assessed, as we did not distinguish fallen and standing deadwood measurement in FAS.

### 2.4.3 Variability of total C stocks in logged forests

Logging is expected to drastically affect deadwood, by increasing deadwood stocks over both space and time (Carlson et al. 2016). While Reduced-impact Logging (RIL) techniques and medium harvest intensity (6-8 trees $ha^{-1}$) were applied across the study sites, the proportion of ground disturbance depends mainly on the size of trees felled (i.e. >60 cm DBH at our study site). No significant difference in deadwood stocks among sites (Figure 2-7) suggests that enhanced deadwood stocks may persist over decades. While decomposition rates of dead trees varied among species and trunk diameter (Harmon et al. 1995; Hérault et al. 2010), stable deadwood stocks are likely to be due to constant input over time due to lagged mortality of damaged trees that can last up to a decade after logging (Blanc et al. 2009; Lussetti et al. 2016; Picard, Gourlet-Fleury, and Forni 2012; Sist et al. 2014).

Total deadwood stock at our study site averaged 22.2 Mg C ha$^{-1}$ (through $FAS_{vis}$), in the spectrum with what has been reported for logged forests in the region (21.9 Mg C ha$^{-1}$ in Pfeifer et al. (2015) and 27.5 Mg C ha$^{-1}$ in Saner et al. (2012) and only form approx. 15% of total C stocks (Figure 2-5B) These last studies were conducted in old-logged (10-50 y.a.l.) forests, while measurements conducted directly after reduced impact logging in an Amazonian forest reports larger values (35 Mg C ha$^{-1}$ in (Keller et al. 2004). Comparing deadwood stocks among forests is hardly feasible, as it depends on many factors such as the amount of incidental damages generated by the different logging techniques (Picard, Gourlet-Fleury, and Forni 2012; Pinard and Putz 1996; Sist and Nguyen-Thé 2002), environmental factors controlling wood decay (Garbarino et al. 2015; Hérault et al. 2010; Weedon et al. 2009), or differences in wood density among species (Yin 1999).

We found significantly lower AGC in the recently logged forest (site 5 y.a.l.) compared to site 12 y.a.l. (Figure 2-5). The high of AGC in site 12 y.a.l. compared to site 5 y.a.l. was due to the large difference of AGC from the medium trees (DBH 30-60) that reached 23 Mg C ha$^{-1}$. While large trees (DBH >60 cm) became the main target of logging, harvesting a few large trees of Dipterocarpaceae is expected to significantly decrease AGC which in turn drive total C storage in logged forests (Sist et al. 2014). In our site, the targeted commercial tree species are the members of the Dipterocarpaceae which contributed approx. 26-40% to total AGC (Figure 2-4). However, AGC (and BGC) will gain along time through the growth of the survivors and recruited trees (Blanc et al. 2009; Piponiot et al. 2016) but this recovery depends on harvesting intensity (Rutishauser et al. 2015).

In our site, the total C stocks averaged 151 Mg C ha$^{-1}$ and ranged from 130 to 174 Mg C ha$^{-1}$. Our results were within the range of total C stocks in the similar logged forest type in Malaysian Borneo (Saner et al. 2012) and the Philippines (Lasco et al. 2006) but lower compared to Malinau forest in Indonesian Borneo (Rozak et al. 2018). The main finding with regard to total C stocks was that the amount of total C stocks in the recently logged forest (site 5 y.a.l.) was lower compared to site 8 y.a.l. and 12 y.a.l. The difference was particularly due to the difference in tree biomass in each site which forms approx. 83% to total C stocks (Figure 2-5). The tree C (AGC and BGC) reached 146, 127, and 105 Mg C ha$^{-1}$ in site 12 y.a.l., 8 y.a.l., and 5 y.a.l., respectively. Assuming pre-logging biomass, logging intensity, and mortality rate are similar among sites, our result confirms the growth of tree C stocks (tree C stocks in 12 y.a.l. > 8 y.a.l. > 5 y.a.l., Figure 2-5) as found elsewhere in tropical logged forests (Blanc et al. 2009; Gourlet-Fleury et al. 2013; Piponiot et al. 2016).

## 2.5 Conclusions

Our study shows that FAS coupled with a locally parametrized wood decay classification can be a good compromise to efficiently estimate deadwood in logged forests. Even though this method inherently holds a bias, setting up a dozen of 100 m-quadrats per hectare enable to accurately estimate total deadwood stocks. With the urgent need to refine forest carbon stocks in international negotiation on climate change, our study provides a first step towards accurate and efficient methods to quantify deadwood stocks in degraded tropical forests. With increasing frequency of extreme natural events and expansion of human activities, accounting for deadwood may rapidly become mandatory in most tropical regions. Further, total C stocks in a recently logged forest (2010) were on average lower than that in the forest that logged in 2007 and 2003. Living trees remain the main C pool in all site (approx. 83% of total C stocks), followed by deadwood (15%), and litter (2%). Our result, therefore, refines an estimation of total C stocks in the different time since logging.

## Acknowledgments

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# Complementary Figures

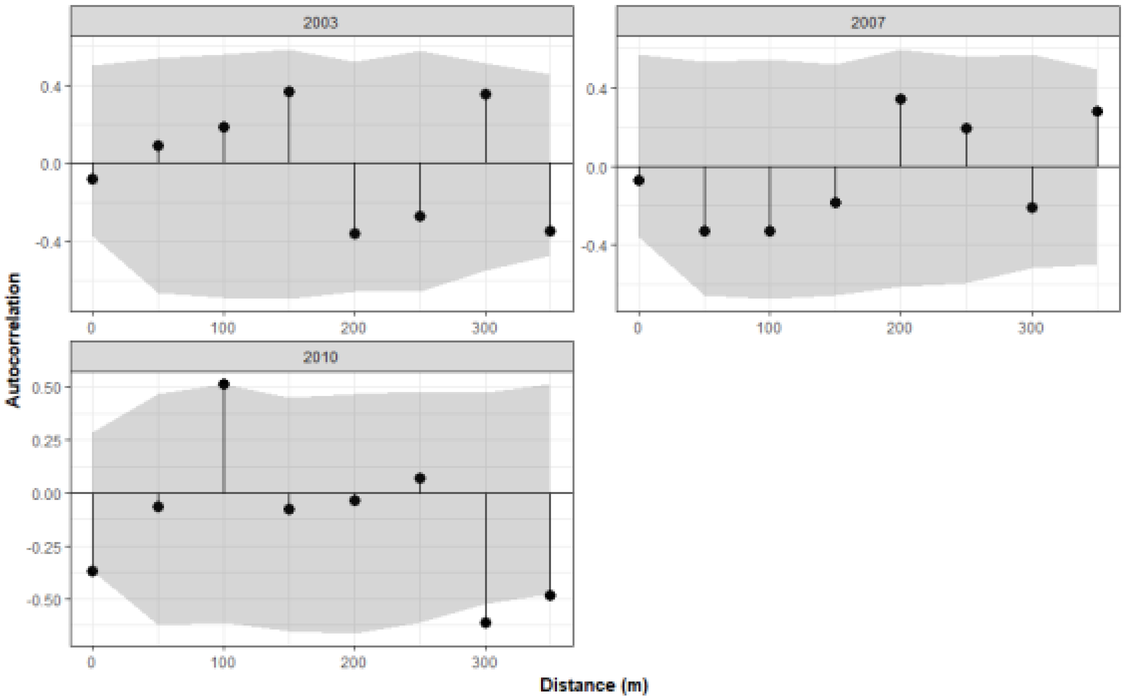



*Figure 2-6 Spatial autocorrelation of deadwood stocks for each site. Grey areas show 95% CI.*

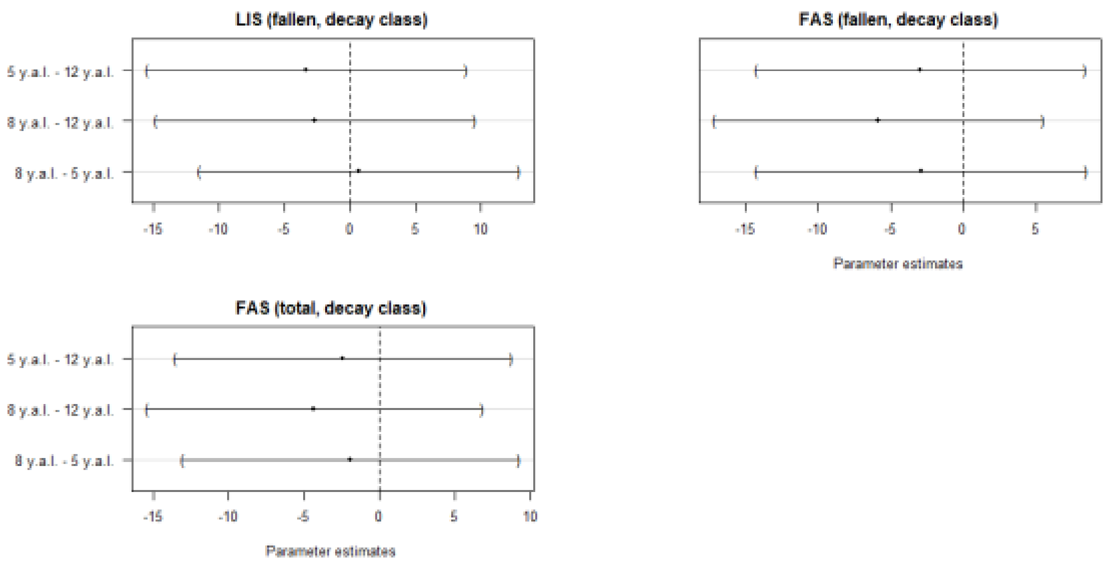



*Figure 2-7 Pair-wise comparisons from Tukey's HSD for fallen deadwood stocks estimated by FAS and LIS and total deadwood stocks estimated by FAS presented with 95% confidence intervals after simple linear model among sites. Any CIs that do not contain 0 are statistically different from zero.*

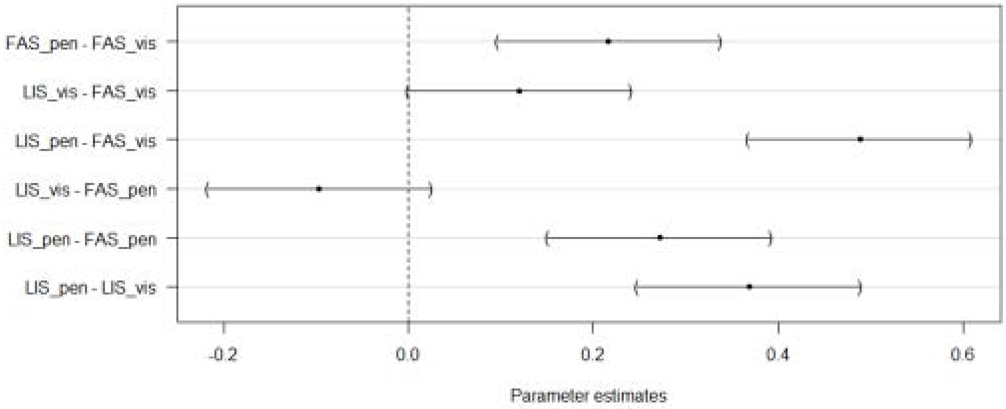



*Figure 2-8 Pair-wise comparisons from Tukey's HSD for the time required among method presented with 95% confidence intervals. Any CIs that do not contain 0 are statistically different from zero.*

# Supplementary Information

### Volume estimation

### Difference among site

Deadwood volume ($m^3$ $ha^{-1}$) was not significantly different among sites (Figure 3-9). Therefore, in line with deadwood stocks analysis (Mg C $ha^{-1}$), each transect and each aggregated subplot might be treated as one sampling unit.

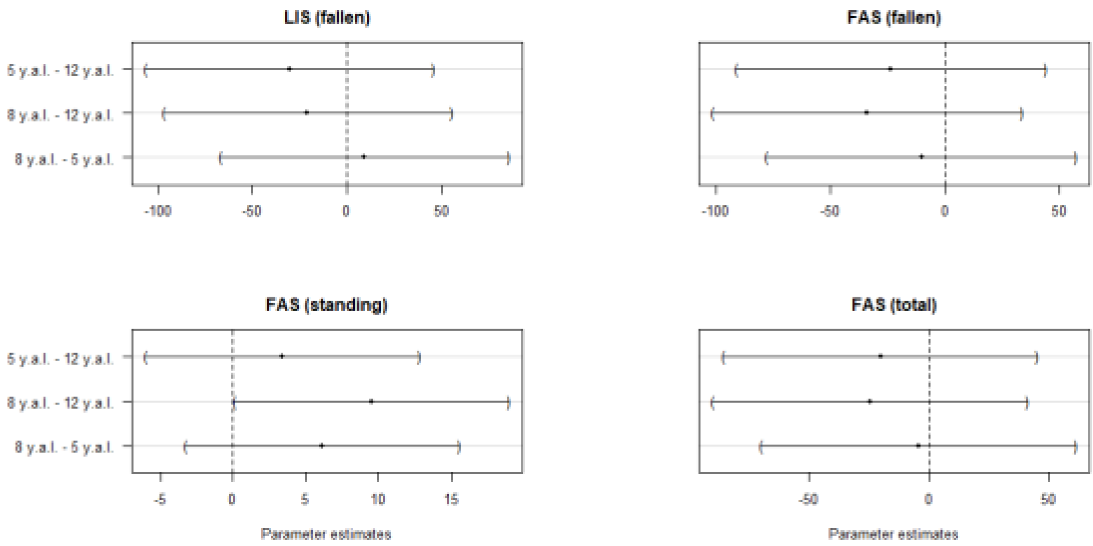



*Figure 2-9 Pair-wise comparisons from Tukey's HSD for fallen deadwood volume estimated by FAS and LIS and total deadwood volume estimated by FAS presented with 95% confidence intervals after simple linear model among sites. Any CIs that do not contain 0 are statistically different from zero.*

### Deadwood volume

Fallen deadwood volume predicted by FAS and LIS was significantly different (Table 3-6, paired t-test: $t_{(14)} = -3.0$, $P = 0.009$). Deadwood volume predicted by LIS was 18% higher than that predicted by FAS. The fallen volume of deadwood estimated by FAS and LIS averaged 344.4 (115.4 – 154.7) and 164.2 (141.4 – 185.6) $m^3$ $ha^{-1}$, respectively.

*Table 2-6 The average of fallen, standing, and total deadwood volume ($m^3$ $ha^{-1}$, 95% CI) estimated by LIS and FAS.*

| Variable | FAS | LIS | Average difference (%) | df | t-value | p-value |
|---|---|---|---|---|---|---|
| **Fallen** | 134.4 (115.4 – 154.7 | 164.2 (141.4 – 185.6) | 18.1 | 14 | -3.0 | 0.009 |
| **Standing** | 4.9 (2.2 – 8.5) | - | - | na | na | na |
| **Total** | 139.3 (121.6 – 159.5) | - | - | na | na | na |

### Efficiency analysis for deadwood volume

Efficiency analysis showed FAS was more efficient than LIS (Table 3-7). However, for site 2010, LIS seems more efficient than FAS as the variance of FAS was higher than LIS.

*Table 2-7 Summary of variance ($S^2$), bias ($Bias^2$), root mean squared error (RMSE) and efficiency (E) for fallen deadwood volume ($m^3$ $ha^{-1}$) each site. $Bias^2$ in LIS assumed to be zero and negative $bias^2$ assigned as zero (*).*

| Site | LIS | FAS |
|---|---|---|
| **$S^2$** | | |
| **12 y.a.l.** | 304.9 | 125.3 |
| **8 y.a.l.** | 3,687.0 | 804.1 |
| **5 y.a.l.** | 2,123.0 | 3,872.4 |
| **All sites** | 1,919.7 | 1,588.6 |
| **$Bias^2$** | | |
| **12 y.a.l.** | 0 | 0* |
| **8 y.a.l.** | 0 | 0* |
| **5 y.a.l.** | 0 | 0* |
| **All sites** | 0 | 0* |
| **RMSE** | | |
| **12 y.a.l.** | 17.5 | 11.2 |
| **8 y.a.l.** | 60.7 | 28.4 |
| **5 y.a.l.** | 46.1 | 62.2 |
| **All sites** | 43.8 | 39.9 |
| **Efficiency** | | |
| **12 y.a.l.** | - | 0.4 |
| **8 y.a.l.** | - | 0.2 |
| **5 y.a.l.** | - | 1.3 |
| **All sites** | - | 0.7 |

### Wood density estimation

### Decay class vs penetrometer to predict deadwood density

Wood densities were significantly different among classes (Anova, $F_{(2,52)} = 17.4$, $P > 0.001$, Table 3-8, Figure 3-10). Decay class 1 (0.47) had higher deadwood density compared to decay class 2 (0.35) and 3 (0.31). Alternatively, wood density was well predicted by penetrometer measurements (Figure 3-11). Our penetrometer model to predict wood density was:

$$WD = 0.23 + 0.36e^{-0.24X}$$

Estimates of wood density using penetrometer model were highly correlated to actual wood density (Figure 3-13).

*Table 2-8 Decay classes and corresponding deadwood density (± 95% CI).*

| Decay class | Description | Number of samples | Average deadwood density (g cm$^{-3}$) |
|---|---|---|---|
| **1** | Extensive bark cover, leaves and fine twigs present, logs relatively undecayed. | 13 | 0.47 (0.42 – 0.51) |
| **2** | No bark and few branch stubs (not moving when pulled), sapwood decaying | 17 | 0.35 (0.31 – 0.38) |
| **3** | Wood often scattered across the soil surface, logs elliptical in cross-section. | 25 | 0.31 (0.28 – 0.34) |

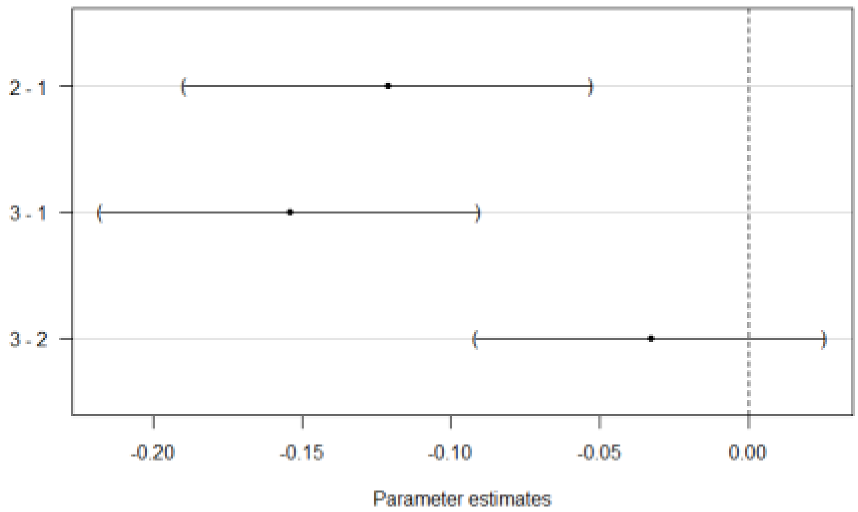



*Figure 2-10 Pair-wise comparisons from Tukey's HSD for each decay class presented with 95% confidence intervals. Any CIs that do not contain 0 are statistically different from zero.*

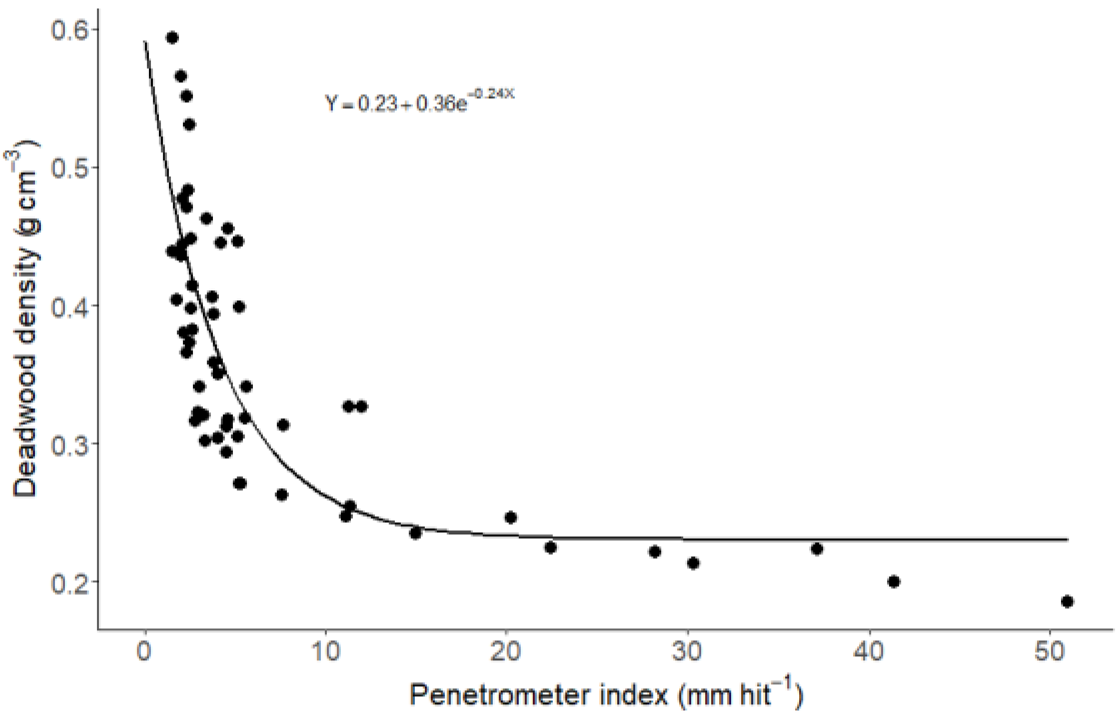



*Figure 2-11 Asymptotic exponential model for wood density prediction using dynamic penetrometer as a function of penetration index.*

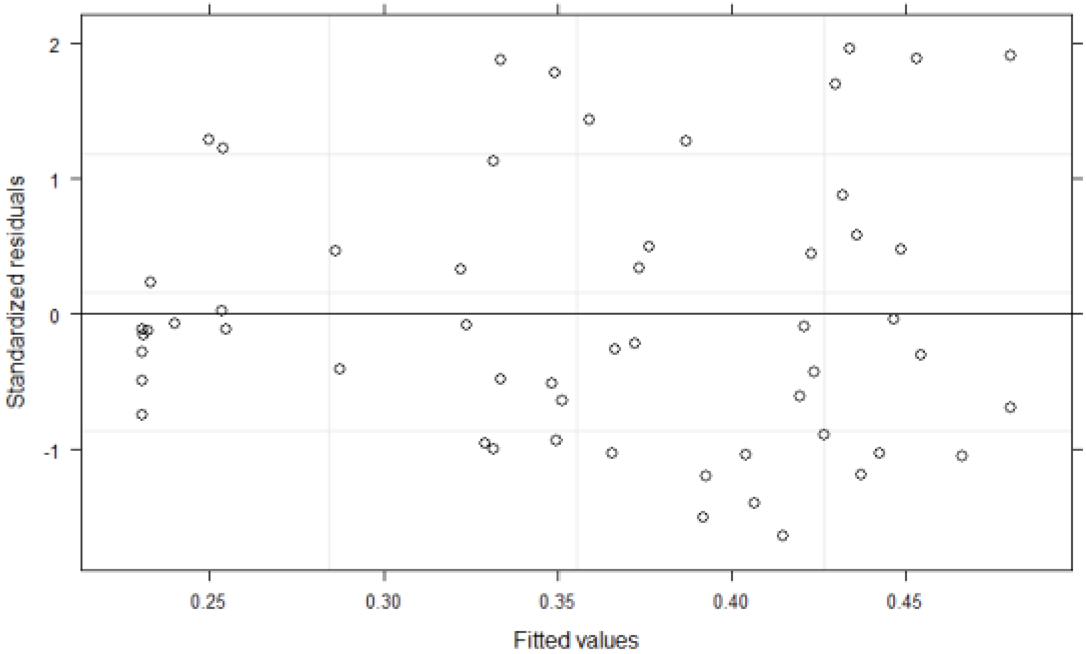



*Figure 2-12 The residual plot of the penetrometer model.*

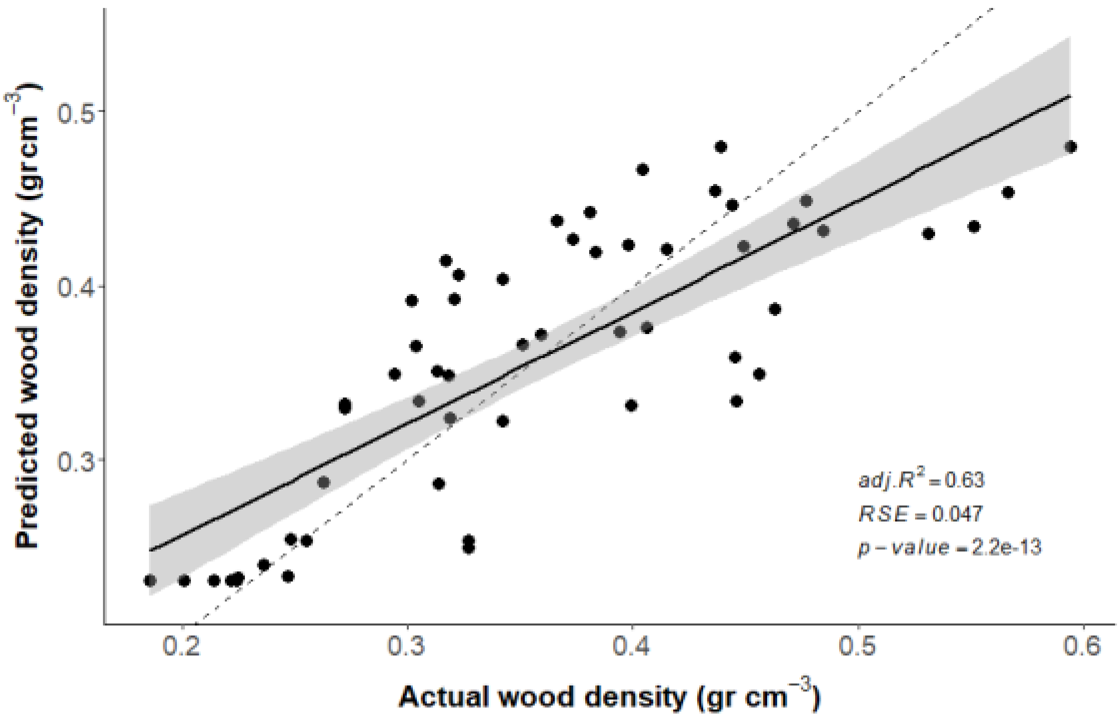



*Figure 2-13 Comparison between actual and predicted wood density by model. The solid black line is a linear model with 95% CI. The dashed black line is a reference line (1:1).*

*Table 2-9 Species list, above-ground carbon (AGC, Mg C ha$^{-1}$), cumulated AGC (Mg C ha$^{-1}$), and cumulated percentage to total AGC (%) in each study site. Tree species were ranked by decreasing size according to their AGC in each site.*

| **No** | **Site 12 y.a.l.** | | | | **Site 8 y.a.l.** | | | | **Site 5 y.a.l.** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Species** | **AGC** | **Cumulated AGC** | **Cumulated %** | **Species** | **AGC** | **Cumulated AGC** | **Cumulated %** | **Species** | **AGC** | **Cumulated AGC** | **Cumulated %** |
| **1** | Shorea parvifolia | 8.5 | 8.5 | 7.0 | Heritiera simplicifolia | 8.2 | 8.2 | 8.1 | Shorea parvifolia | 10.5 | 10.5 | 12.9 |
| **2** | Hopea cernua | 8.0 | 16.5 | 13.7 | Syzygium sp. | 7.5 | 15.7 | 15.6 | Chaetocarpus castanicarpus | 6.1 | 16.6 | 20.4 |
| **3** | Syzygium sp. | 8.0 | 24.5 | 20.3 | Shorea pinanga | 7.1 | 22.8 | 22.7 | Eusideroxylon zwageri | 5.5 | 22.1 | 27.2 |
| **4** | Gluta renghas | 7.8 | 32.3 | 26.7 | Shorea beccariana | 3.9 | 26.7 | 26.6 | Diospyros borneensis | 3.8 | 25.8 | 31.9 |
| **5** | Dipterocarpus grandiflorus | 6.2 | 38.5 | 31.8 | Hopea cernua | 3.9 | 30.6 | 30.5 | Parashorea tomentella | 3.7 | 29.5 | 36.4 |
| **6** | Koompassia malaccensis | 5.9 | 44.4 | 36.7 | Lithocarpus sp. | 3.8 | 34.4 | 34.3 | Lithocarpus sp. | 3.5 | 33.0 | 40.8 |
| **7** | Pertusadina sp. | 4.9 | 49.3 | 40.7 | Shorea atrinervosa | 3.8 | 38.2 | 38.0 | Litsea sp. | 3.0 | 36.1 | 44.5 |
| **8** | Chaetocarpus castanicarpus | 4.4 | 53.7 | 44.3 | Dipterocarpus eurhynchus | 3.1 | 41.2 | 41.1 | Artocarpus lanceifolius | 2.5 | 38.5 | 47.5 |
| **9** | Shorea beccariana | 4.2 | 57.9 | 47.9 | Shorea parvifolia | 3.0 | 44.3 | 44.1 | Syzygium sp. | 2.1 | 40.6 | 50.1 |
| **10** | Shorea atrinervosa | 4.2 | 62.1 | 51.3 | Palaquium calophyllum | 3.0 | 47.2 | 47.1 | Santiria sp. | 2.0 | 42.6 | 52.6 |
| **11** | Irvingia malayana | 3.6 | 65.7 | 54.3 | Shorea sp. | 2.4 | 49.6 | 49.5 | Octomeles sumatrana | 1.9 | 44.5 | 54.9 |
| **12** | Madhuca malaccensis | 3.5 | 69.3 | 57.2 | Xanthophyllum sp. | 2.3 | 52.0 | 51.8 | Shorea sp. | 1.8 | 46.3 | 57.1 |
| **13** | Heritiera simplicifolia | 3.2 | 72.5 | 59.9 | Madhuca malaccensis | 2.1 | 54.1 | 53.9 | Shorea leprosula | 1.7 | 48.0 | 59.3 |
| **14** | Xanthophyllum sp. | 3.0 | 75.5 | 62.4 | Santiria sp. | 2.1 | 56.2 | 56.0 | Koordersiodendron pinnatum | 1.7 | 49.7 | 61.4 |
| **15** | Sindora velutina | 3.0 | 78.5 | 64.9 | Xerospermum sp. | 1.9 | 58.1 | 57.9 | Shorea smithiana | 1.7 | 51.4 | 63.4 |
| **16** | Shorea maxwelliana | 2.5 | 81.1 | 67.0 | Vatica nitens | 1.9 | 59.9 | 59.7 | Aglaia sp. | 1.6 | 53.0 | 65.4 |

| No | Site 12 y.a.l. | | | | Site 8 y.a.l. | | | | Site 5 y.a.l. | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Species | AGC | Cumulated AGC | Cumulated % | Species | AGC | Cumulated AGC | Cumulated % | Species | AGC | Cumulated AGC | Cumulated % |
| **17** | Shorea sp. | 2.5 | 83.5 | 69.1 | Alseodaphne sp. | 1.8 | 61.8 | 61.6 | Glochidion sp. | 1.5 | 54.5 | 67.2 |
| **18** | Palaquium dasyphyllum | 2.4 | 85.9 | 71.0 | Dipterocarpus grandiflorus | 1.8 | 63.5 | 63.3 | Durio dulcis | 1.4 | 55.9 | 68.9 |
| **19** | Scaphium macropodum | 2.4 | 88.3 | 73.0 | Drypetes kikir | 1.5 | 65.1 | 64.9 | Drypetes kikir | 1.2 | 57.1 | 70.4 |
| **20** | Vatica nitens | 2.3 | 90.6 | 74.9 | Dipterocarpus stellatus | 1.5 | 66.5 | 66.3 | Dryobalanops beccarii | 1.1 | 58.1 | 71.8 |
| **21** | Neoscortechinia sp. | 2.2 | 92.9 | 76.7 | Cotylelobium melanoxylon | 1.4 | 68.0 | 67.7 | Dehaasia sp. | 1.1 | 59.2 | 73.1 |
| **22** | Allantospermum borneense | 2.2 | 95.0 | 78.5 | Irvingia malayana | 1.4 | 69.4 | 69.2 | Toona sureni | 1.0 | 60.2 | 74.3 |
| **23** | Shorea angustifolia | 2.0 | 97.0 | 80.2 | Dipterocarpus acutangulus | 1.4 | 70.8 | 70.6 | Artocarpus anisophyllus | 1.0 | 61.2 | 75.5 |
| **24** | Dipterocarpus crinitus | 2.0 | 99.0 | 81.8 | Vatica oblongifolia | 1.3 | 72.1 | 71.9 | Diospyros sp. | 0.9 | 62.1 | 76.6 |
| **25** | Canarium sp. | 1.9 | 100.9 | 83.4 | Buchanania sp. | 1.3 | 73.4 | 73.1 | Macaranga hypoleuca | 0.9 | 63.0 | 77.8 |
| **26** | Santiria sp. | 1.6 | 102.5 | 84.7 | Palaquium dasyphyllum | 1.1 | 74.4 | 74.2 | Drypetes longifolia | 0.9 | 63.9 | 78.8 |
| **27** | Dialium indum | 1.2 | 103.7 | 85.7 | Calophyllum inophyllum | 0.9 | 75.4 | 75.1 | Cyathocalyx sp. | 0.7 | 64.6 | 79.7 |
| **28** | Shorea macroptera | 0.9 | 104.6 | 86.5 | Shorea angustifolia | 0.9 | 76.3 | 76.1 | Xanthophyllum sp. | 0.7 | 65.3 | 80.6 |
| **29** | Garcinia celebica | 0.9 | 105.5 | 87.2 | Artocarpus anisophyllus | 0.9 | 77.2 | 76.9 | Elateriospermum tapos | 0.7 | 65.9 | 81.4 |
| **30** | Barringtonia pendula | 0.9 | 106.4 | 88.0 | Scaphium macropodum | 0.8 | 78.0 | 77.8 | Antidesma sp. | 0.7 | 66.6 | 82.2 |
| **31** | Barringtonia macrostachya | 0.9 | 107.3 | 88.7 | Santiria griffithii | 0.8 | 78.8 | 78.6 | Nephelium sp. | 0.6 | 67.3 | 83.0 |
| **32** | Elaeocarpus sp. | 0.8 | 108.1 | 89.4 | Barringtonia pendula | 0.8 | 79.6 | 79.3 | Ficus geocarpa | 0.6 | 67.8 | 83.8 |
| **33** | Lophopetalum sp. | 0.8 | 108.9 | 90.0 | Dipterocarpus verrucosus | 0.8 | 80.4 | 80.1 | Duabanga moluccana | 0.6 | 68.4 | 84.5 |
| **34** | Lithocarpus sp. | 0.8 | 109.8 | 90.7 | Lophopetalum | 0.7 | 81.1 | 80.8 | Aporosa sp. | 0.6 | 69.0 | 85.2 |

| No | Site 12 y.a.l. | | | | Site 8 y.a.l. | | | | Site 5 y.a.l. | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Species | AGC | Cumulated AGC | Cumulated % | Species | AGC | Cumulated AGC | Cumulated % | Species | AGC | Cumulated AGC | Cumulated % |
| | | | | | javanicum | | | | | | | |
| **35** | Palaquium calophyllum | 0.8 | 110.6 | 91.4 | Tetramerista glabra | 0.7 | 81.8 | 81.6 | Artocarpus elasticus | 0.6 | 69.6 | 85.9 |
| **36** | Myristica villosa | 0.7 | 111.3 | 92.0 | Barringtonia macrostachya | 0.7 | 82.5 | 82.2 | Endiandra sp. | 0.6 | 70.1 | 86.6 |
| **37** | Cotylelobium melanoxylon | 0.7 | 112.0 | 92.6 | Litsea sp. | 0.7 | 83.2 | 82.9 | Knema laurina | 0.5 | 70.7 | 87.2 |
| **38** | Chionanthus sp. | 0.6 | 112.6 | 93.1 | Anisophyllea sp. | 0.6 | 83.8 | 83.6 | Hydnocarpus sp. | 0.5 | 71.2 | 87.9 |
| **39** | Shorea collaris | 0.6 | 113.2 | 93.6 | Teijsmanniodendron sp. | 0.6 | 84.5 | 84.2 | Polyalthia sp. | 0.5 | 71.7 | 88.4 |
| **40** | Calophyllum inophyllum | 0.6 | 113.8 | 94.0 | Shorea retusa | 0.6 | 85.1 | 84.8 | Santiria griffithii | 0.5 | 72.1 | 89.0 |
| **41** | Gymnacranthera sp. | 0.5 | 114.3 | 94.5 | Chaetocarpus castanicarpus | 0.6 | 85.7 | 85.4 | Palaquium calophyllum | 0.4 | 72.5 | 89.5 |
| **42** | Shorea agami | 0.5 | 114.8 | 94.9 | Sindora sp. | 0.6 | 86.3 | 86.0 | Scaphium macropodum | 0.4 | 72.9 | 90.0 |
| **43** | Vatica oblongifolia | 0.5 | 115.3 | 95.3 | Canarium sp. | 0.6 | 86.8 | 86.5 | Aglaia tomentosa | 0.4 | 73.3 | 90.5 |
| **44** | Diospyros sp. | 0.5 | 115.7 | 95.6 | Dialium indum | 0.6 | 87.4 | 87.1 | Dialium indum | 0.4 | 73.7 | 91.0 |
| **45** | Teijsmanniodendron sp. | 0.4 | 116.1 | 96.0 | Palaquium sp. | 0.5 | 87.9 | 87.6 | Knema sp. | 0.4 | 74.1 | 91.4 |
| **46** | Palaquium sp. | 0.3 | 116.5 | 96.3 | Pentace adenophora | 0.5 | 88.4 | 88.1 | Macaranga gigantea | 0.4 | 74.4 | 91.9 |
| **47** | Gironniera nervosa | 0.3 | 116.8 | 96.5 | Shorea almon | 0.5 | 88.8 | 88.5 | Croton argyratus | 0.3 | 74.8 | 92.3 |
| **48** | Anisoptera costata | 0.3 | 117.1 | 96.8 | Strombosia sp. | 0.4 | 89.3 | 89.0 | Allophyllus cobbe | 0.3 | 75.1 | 92.7 |
| **49** | Polyalthia sumatrana | 0.3 | 117.4 | 97.0 | Semecarpus sp. | 0.4 | 89.7 | 89.4 | Ochanostachys amentacea | 0.3 | 75.4 | 93.1 |
| **50** | Litsea sp. | 0.3 | 117.6 | 97.2 | Garcinia sp. | 0.4 | 90.1 | 89.8 | Myristica villosa | 0.3 | 75.7 | 93.4 |
| **51** | Blumeodendron sp. | 0.3 | 117.9 | 97.5 | Chionanthus sp. | 0.4 | 90.5 | 90.3 | Polyalthia rumphii | 0.3 | 76.0 | 93.8 |
| **52** | Semecarpus sp. | 0.3 | 118.2 | 97.7 | Pternandra sp. | 0.4 | 90.9 | 90.7 | Dimocarpus longan | 0.3 | 76.3 | 94.2 |
| **53** | Gomphia serrata | 0.3 | 118.5 | 97.9 | Shorea macroptera | 0.4 | 91.3 | 91.0 | Canarium sp. | 0.3 | 76.5 | 94.5 |

| No | Site 12 y.a.l. | | | | Site 8 y.a.l. | | | | Site 5 y.a.l. | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Species | AGC | Cumulated AGC | Cumulated % | Species | AGC | Cumulated AGC | Cumulated % | Species | AGC | Cumulated AGC | Cumulated % |
| **54** | Memecylon sp. | 0.2 | 118.7 | 98.1 | Knema sp. | 0.4 | 91.7 | 91.4 | Kayea borneensis | 0.3 | 76.8 | 94.8 |
| **55** | Knema sp. | 0.2 | 118.9 | 98.3 | Knema furfuracea | 0.3 | 92.1 | 91.8 | Garcinia sp. | 0.2 | 77.0 | 95.1 |
| **56** | Macaranga gigantea | 0.2 | 119.1 | 98.4 | Rhodamnia sp. | 0.3 | 92.4 | 92.1 | Gluta renghas | 0.2 | 77.3 | 95.4 |
| **57** | Gonystylus macrophyllus | 0.2 | 119.3 | 98.6 | Gluta renghas | 0.3 | 92.7 | 92.4 | Dillenia sp. | 0.2 | 77.5 | 95.6 |
| **58** | Pimelodendron sp. | 0.1 | 119.4 | 98.7 | Artocarpus integer | 0.3 | 93.1 | 92.8 | Madhuca sericea | 0.2 | 77.7 | 95.9 |
| **59** | Mallotus penangensis | 0.1 | 119.5 | 98.8 | Dacryodes rostrata | 0.3 | 93.4 | 93.1 | Sindora leiocarpa | 0.2 | 77.9 | 96.2 |
| **60** | Buchanania sp. | 0.1 | 119.7 | 98.9 | Neoscortechinia sp. | 0.3 | 93.7 | 93.4 | Semecarpus sp. | 0.2 | 78.1 | 96.4 |
| **61** | Parashorea smythiesii | 0.1 | 119.8 | 99.0 | Madhuca sericea | 0.3 | 94.0 | 93.7 | Neoscortechinia sp. | 0.2 | 78.2 | 96.6 |
| **62** | Santiria griffithii | 0.1 | 119.9 | 99.1 | Ochanostachys amentacea | 0.3 | 94.2 | 93.9 | Endospermum diadenum | 0.2 | 78.4 | 96.8 |
| **63** | Dacryodes rostrata | 0.1 | 120.0 | 99.2 | Gonystylus macrophyllus | 0.2 | 94.5 | 94.2 | Sterculia sp. | 0.2 | 78.6 | 97.0 |
| **64** | Dipterocarpus stellatus | 0.1 | 120.1 | 99.3 | Gironniera nervosa | 0.2 | 94.7 | 94.4 | Mallotus sp. | 0.2 | 78.7 | 97.2 |
| **65** | Macaranga hypoleuca | 0.1 | 120.2 | 99.4 | Nauclea subdita | 0.2 | 94.9 | 94.6 | Paranephelium sp. | 0.1 | 78.9 | 97.4 |
| **66** | Sarcotheca sp. | 0.1 | 120.3 | 99.4 | Campnosperma sp. | 0.2 | 95.2 | 94.9 | Polyalthia sumatrana | 0.1 | 79.0 | 97.5 |
| **67** | Hypobathrum sp. | 0.1 | 120.4 | 99.5 | Gonystylus sp. | 0.2 | 95.4 | 95.1 | Baccaurea sumatrana | 0.1 | 79.1 | 97.7 |
| **68** | Artocarpus elasticus | 0.1 | 120.5 | 99.6 | Myristica villosa | 0.2 | 95.6 | 95.3 | Ardisia sp. | 0.1 | 79.3 | 97.8 |
| **69** | Mesua sp. | 0.1 | 120.6 | 99.6 | Ardisia sp. | 0.2 | 95.8 | 95.5 | Calophyllum inophyllum | 0.1 | 79.4 | 98.0 |
| **70** | Xylopia ferruginea | 0.1 | 120.6 | 99.7 | Knema laurina | 0.2 | 96.0 | 95.7 | Madhuca malaccensis | 0.1 | 79.5 | 98.2 |
| **71** | Sloanea sp. | 0.1 | 120.7 | 99.8 | Moultonianthus sp. | 0.2 | 96.2 | 95.9 | Blumeodendron sp. | 0.1 | 79.6 | 98.3 |
| **72** | Horsfieldia sp. | 0.0 | 120.7 | 99.8 | Durio graveolens | 0.2 | 96.4 | 96.0 | Memecylon sp. | 0.1 | 79.7 | 98.4 |

| No | Site 12 y.a.l. | | | | Site 8 y.a.l. | | | | Site 5 y.a.l. | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Species | AGC | Cumulated AGC | Cumulated % | Species | AGC | Cumulated AGC | Cumulated % | Species | AGC | Cumulated AGC | Cumulated % |
| **73** | Knema furfuracea | 0.0 | 120.8 | 99.8 | Polyalthia sumatrana | 0.2 | 96.5 | 96.2 | Shorea johorensis | 0.1 | 79.8 | 98.5 |
| **74** | Cleistanthus sp. | 0.0 | 120.8 | 99.9 | Dipterocarpus crinitus | 0.2 | 96.7 | 96.4 | Allantospermum borneense | 0.1 | 79.9 | 98.7 |
| **75** | Archidendron sp. | 0.0 | 120.8 | 99.9 | Sindora velutina | 0.2 | 96.9 | 96.6 | Cleistanthus sp. | 0.1 | 80.0 | 98.8 |
| **76** | Dipterocarpus sp. | 0.0 | 120.9 | 99.9 | Vatica umbonata | 0.1 | 97.0 | 96.7 | Enicosanthum sp. | 0.1 | 80.1 | 98.9 |
| **77** | Ardisia sp. | 0.0 | 120.9 | 99.9 | Stemonurus sp. | 0.1 | 97.2 | 96.8 | Vatica umbonata | 0.1 | 80.2 | 98.9 |
| **78** | Drypetes kikir | 0.0 | 120.9 | 99.9 | Sarcotheca sp. | 0.1 | 97.3 | 97.0 | Dacryodes rostrata | 0.1 | 80.2 | 99.0 |
| **79** | Artocarpus anisophyllus | 0.0 | 120.9 | 100.0 | Rothmannia sp. | 0.1 | 97.4 | 97.1 | Aporosa octandra | 0.1 | 80.3 | 99.1 |
| **80** | Xylopia sp. | 0.0 | 121.0 | 100.0 | Artocarpus elasticus | 0.1 | 97.6 | 97.3 | Vatica nitens | 0.1 | 80.3 | 99.2 |
| **81** | Aporosa sp. | 0.0 | 121.0 | 100.0 | Dillenia sp. | 0.1 | 97.7 | 97.4 | Baccaurea macrocarpa | 0.1 | 80.4 | 99.2 |
| **82** | Hydnocarpus sp. | 0.0 | 121.0 | 100.0 | Anisoptera costata | 0.1 | 97.8 | 97.5 | Cynometra sp. | 0.1 | 80.5 | 99.3 |
| **83** | Macaranga triloba | 0.0 | 121.0 | 100.0 | Endiandra sp. | 0.1 | 97.9 | 97.6 | Dendrocnide sp. | 0.1 | 80.5 | 99.4 |
| **84** | | | | | Durio dulcis | 0.1 | 98.0 | 97.7 | Palaquium sp. | 0.0 | 80.6 | 99.4 |
| **85** | | | | | Knema elmeri | 0.1 | 98.1 | 97.8 | Dracontomelon dao | 0.0 | 80.6 | 99.5 |
| **86** | | | | | Drimycarpus sp. | 0.1 | 98.2 | 97.9 | Chionanthus sp. | 0.0 | 80.6 | 99.6 |
| **87** | | | | | Madhuca kingiana | 0.1 | 98.3 | 98.0 | Croton sp. | 0.0 | 80.7 | 99.6 |
| **88** | | | | | Dipterocarpus confertus | 0.1 | 98.4 | 98.1 | Gomphia serrata | 0.0 | 80.7 | 99.6 |
| **89** | | | | | Shorea smithiana | 0.1 | 98.5 | 98.2 | Popowia hirta | 0.0 | 80.8 | 99.7 |
| **90** | | | | | Heritiera sp. | 0.1 | 98.6 | 98.2 | Magnolia tsiampacca | 0.0 | 80.8 | 99.7 |
| **91** | | | | | Blumeodendron sp. | 0.1 | 98.6 | 98.3 | Cratoxylum sumatranum | 0.0 | 80.8 | 99.8 |
| **92** | | | | | Pimelodendron sp. | 0.1 | 98.7 | 98.4 | Mezzettia parviflora | 0.0 | 80.9 | 99.8 |

| No | Site 12 y.a.l. | | | | Site 8 y.a.l. | | | | Site 5 y.a.l. | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Species | AGC | Cumulated AGC | Cumulated % | Species | AGC | Cumulated AGC | Cumulated % | Species | AGC | Cumulated AGC | Cumulated % |
| **93** | | | | | Pometia pinnata | 0.1 | 98.8 | 98.5 | Hopea pachycarpa | 0.0 | 80.9 | 99.8 |
| **94** | | | | | Shorea exelliptica | 0.1 | 98.8 | 98.5 | Dipterocarpus grandiflorus | 0.0 | 80.9 | 99.9 |
| **95** | | | | | Cephalomappa beccariana | 0.1 | 98.9 | 98.6 | Sarcotheca sp. | 0.0 | 80.9 | 99.9 |
| **96** | | | | | Tabernaemontana sp. | 0.1 | 99.0 | 98.6 | Payena acuminata | 0.0 | 80.9 | 99.9 |
| **97** | | | | | Diospyros borneensis | 0.1 | 99.0 | 98.7 | Magnolia liliifera | 0.0 | 81.0 | 99.9 |
| **98** | | | | | Sageraea sp. | 0.1 | 99.1 | 98.8 | Mallotus muticus | 0.0 | 81.0 | 99.9 |
| **99** | | | | | Garcinia celebica | 0.1 | 99.2 | 98.8 | Macaranga winkleri | 0.0 | 81.0 | 100.0 |
| **100** | | | | | Macaranga beccariana | 0.1 | 99.2 | 98.9 | Polyalthia lateriflora | 0.0 | 81.0 | 100.0 |
| **101** | | | | | Dehaasia sp. | 0.1 | 99.3 | 98.9 | Palaquium dasyphyllum | 0.0 | 81.0 | 100.0 |
| **102** | | | | | Dimocarpus longan | 0.1 | 99.3 | 99.0 | Litsea oppositifolia | 0.0 | 81.0 | 100.0 |
| **103** | | | | | Baccaurea macrocarpa | 0.1 | 99.4 | 99.0 | | | | |
| **104** | | | | | Macaranga gigantea | 0.1 | 99.4 | 99.1 | | | | |
| **105** | | | | | Shorea pauciflora | 0.1 | 99.5 | 99.2 | | | | |
| **106** | | | | | Aporosa octandra | 0.0 | 99.5 | 99.2 | | | | |
| **107** | | | | | Polyalthia rumphii | 0.0 | 99.6 | 99.2 | | | | |
| **108** | | | | | Drypetes longifolia | 0.0 | 99.6 | 99.3 | | | | |
| **109** | | | | | Koompassia malaccensis | 0.0 | 99.7 | 99.3 | | | | |
| **110** | | | | | Aglaia sp. | 0.0 | 99.7 | 99.4 | | | | |
| **111** | | | | | Aporosa sp. | 0.0 | 99.7 | 99.4 | | | | |
| **112** | | | | | Sloanea sp. | 0.0 | 99.8 | 99.4 | | | | |

| No | Site 12 y.a.l. | | | | Site 8 y.a.l. | | | | Site 5 y.a.l. | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Species | AGC | Cumulated AGC | Cumulated % | Species | AGC | Cumulated AGC | Cumulated % | Species | AGC | Cumulated AGC | Cumulated % |
| **113** | | | | | Kayea borneensis | 0.0 | 99.8 | 99.5 | | | | |
| **114** | | | | | Mallotus penangensis | 0.0 | 99.8 | 99.5 | | | | |
| **115** | | | | | Sterculia sp. | 0.0 | 99.9 | 99.6 | | | | |
| **116** | | | | | Bouea sp. | 0.0 | 99.9 | 99.6 | | | | |
| **117** | | | | | Symplocos sp. | 0.0 | 99.9 | 99.6 | | | | |
| **118** | | | | | Heritiera elata | 0.0 | 100.0 | 99.6 | | | | |
| **119** | | | | | Alangium sp. | 0.0 | 100.0 | 99.7 | | | | |
| **120** | | | | | Macaranga hypoleuca | 0.0 | 100.0 | 99.7 | | | | |
| **121** | | | | | Artocarpus lanceifolius | 0.0 | 100.1 | 99.7 | | | | |
| **122** | | | | | Enicosanthum sp. | 0.0 | 100.1 | 99.8 | | | | |
| **123** | | | | | Shorea agami | 0.0 | 100.1 | 99.8 | | | | |
| **124** | | | | | Mezzettia parviflora | 0.0 | 100.1 | 99.8 | | | | |
| **125** | | | | | Popowia hirta | 0.0 | 100.2 | 99.8 | | | | |
| **126** | | | | | Parinari sp. | 0.0 | 100.2 | 99.8 | | | | |
| **127** | | | | | Elaeocarpus sp. | 0.0 | 100.2 | 99.9 | | | | |
| **128** | | | | | Sarcotheca diversifolia | 0.0 | 100.2 | 99.9 | | | | |
| **129** | | | | | Mangifera pajang | 0.0 | 100.2 | 99.9 | | | | |
| **130** | | | | | Pleiocarpidia sp. | 0.0 | 100.2 | 99.9 | | | | |
| **131** | | | | | Antidesma sp. | 0.0 | 100.3 | 99.9 | | | | |
| **132** | | | | | Mesua sp. | 0.0 | 100.3 | 99.9 | | | | |
| **133** | | | | | Actinodaphne sp. | 0.0 | 100.3 | 100.0 | | | | |
| **134** | | | | | Myristica sp. | 0.0 | 100.3 | 100.0 | | | | |
| **135** | | | | | Diospyros sp. | 0.0 | 100.3 | 100.0 | | | | |

| No | Site 12 y.a.l. | | | | Site 8 y.a.l. | | | | Site 5 y.a.l. | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Species** | **AGC** | **Cumulated AGC** | **Cumulated %** | **Species** | **AGC** | **Cumulated AGC** | **Cumulated %** | **Species** | **AGC** | **Cumulated AGC** | **Cumulated %** |
| **136** | | | | | Archidendron sp. | 0.0 | 100.3 | 100.0 | | | | |
| **137** | | | | | Aporosa nitida | 0.0 | 100.3 | 100.0 | | | | |

*Table 2-10 Family list, above-ground carbon (AGC, Mg C ha$^{-1}$), cumulated AGC (Mg C ha$^{-1}$), and cumulated percentage to total AGC (%) in each study site. Tree families were ranked by decreasing size according to their AGC in each site.*

| **No** | **Site 12 y.a.l.** | | | | **Site 8 y.a.l.** | | | | **Site 5 y.a.l.** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Family** | **AGC** | **Cumulated AGC** | **Cumulated %** | **Family** | **AGC** | **Cumulated AGC** | **Cumulated %** | **Family** | **AGC** | **Cumulated AGC** | **Cumulated %** |
| **1** | Dipterocarpaceae | 46.2 | 46.2 | 38.2 | Dipterocarpaceae | 40.3 | 40.3 | 40.2 | Dipterocarpaceae | 20.7 | 20.7 | 25.6 |
| **2** | Fabaceae | 10.1 | 56.3 | 46.5 | Malvaceae | 9.9 | 50.2 | 50.1 | Lauraceae | 10.2 | 30.8 | 38.2 |
| **3** | Anacardiaceae | 8.2 | 64.5 | 53.3 | Myrtaceae | 7.9 | 58.1 | 57.9 | Peraceae | 6.1 | 36.9 | 45.8 |
| **4** | Myrtaceae | 8.0 | 72.5 | 59.9 | Sapotaceae | 7.1 | 65.2 | 65.0 | Ebenaceae | 4.7 | 41.6 | 51.6 |
| **5** | Sapotaceae | 7.1 | 79.5 | 65.7 | Fagaceae | 3.8 | 69.0 | 68.8 | Moraceae | 4.6 | 46.2 | 57.2 |
| **6** | Malvaceae | 5.6 | 85.1 | 70.4 | Burseraceae | 3.8 | 72.8 | 72.5 | Fagaceae | 3.5 | 49.7 | 61.6 |
| **7** | Rubiaceae | 5.0 | 90.1 | 74.5 | Lauraceae | 2.7 | 75.4 | 75.2 | Phyllanthaceae | 3.0 | 52.7 | 65.4 |
| **8** | Peraceae | 4.4 | 94.5 | 78.1 | Anacardiaceae | 2.4 | 77.9 | 77.6 | Meliaceae | 3.0 | 55.8 | 69.1 |
| **9** | Burseraceae | 3.8 | 98.3 | 81.2 | Polygalaceae | 2.3 | 80.2 | 79.9 | Euphorbiaceae | 2.9 | 58.7 | 72.8 |
| **10** | Irvingiaceae | 3.6 | 101.9 | 84.2 | Sapindaceae | 2.0 | 82.2 | 81.9 | Burseraceae | 2.8 | 61.5 | 76.2 |
| **11** | Euphorbiaceae | 3.1 | 105.0 | 86.8 | Putranjivaceae | 1.6 | 83.8 | 83.5 | Anacardiaceae | 2.2 | 63.7 | 78.9 |
| **12** | Polygalaceae | 3.0 | 108.0 | 89.3 | Lecythidaceae | 1.5 | 85.2 | 85.0 | Myrtaceae | 2.1 | 65.7 | 81.5 |
| **13** | Ixonanthaceae | 2.2 | 110.2 | 91.1 | Irvingiaceae | 1.4 | 86.7 | 86.4 | Putranjivaceae | 2.1 | 67.8 | 84.0 |
| **14** | Lecythidaceae | 1.7 | 111.9 | 92.5 | Moraceae | 1.3 | 88.0 | 87.7 | Malvaceae | 1.9 | 69.8 | 86.5 |
| **15** | Myristicaceae | 1.6 | 113.5 | 93.8 | Fabaceae | 1.3 | 89.3 | 89.0 | Tetramelaceae | 1.9 | 71.6 | 88.8 |
| **16** | Clusiaceae | 0.9 | 114.4 | 94.5 | Myristicaceae | 1.2 | 90.6 | 90.3 | Annonaceae | 1.8 | 73.4 | 91.0 |
| **17** | Elaeocarpaceae | 0.9 | 115.3 | 95.3 | Calophyllaceae | 1.0 | 91.6 | 91.3 | Myristicaceae | 1.2 | 74.6 | 92.5 |
| **18** | Celastraceae | 0.8 | 116.1 | 95.9 | Euphorbiaceae | 0.9 | 92.5 | 92.2 | Sapindaceae | 1.1 | 75.7 | 93.8 |
| **19** | Fagaceae | 0.8 | 116.9 | 96.6 | Celastraceae | 0.7 | 93.2 | 92.9 | Sapotaceae | 0.8 | 76.5 | 94.9 |
| **20** | Calophyllaceae | 0.7 | 117.6 | 97.2 | Tetrameristaceae | 0.7 | 93.9 | 93.6 | Polygalaceae | 0.7 | 77.2 | 95.7 |
| **21** | Oleaceae | 0.6 | 118.2 | 97.7 | Olacaceae | 0.7 | 94.6 | 94.3 | Fabaceae | 0.6 | 77.9 | 96.5 |

| No | Site 12 y.a.l. | | | | Site 8 y.a.l. | | | | Site 5 y.a.l. | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Family** | **AGC** | **Cumulated AGC** | **Cumulated %** | **Family** | **AGC** | **Cumulated AGC** | **Cumulated %** | **Family** | **AGC** | **Cumulated AGC** | **Cumulated %** |
| **22** | Ebenaceae | 0.5 | 118.6 | 98.0 | Anisophylleaceae | 0.6 | 95.3 | 94.9 | Lythraceae | 0.6 | 78.5 | 97.3 |
| **23** | Lamiaceae | 0.4 | 119.1 | 98.4 | Lamiaceae | 0.6 | 95.9 | 95.6 | Achariaceae | 0.5 | 79.0 | 97.9 |
| **24** | Annonaceae | 0.4 | 119.5 | 98.7 | Peraceae | 0.6 | 96.5 | 96.2 | Calophyllaceae | 0.4 | 79.4 | 98.4 |
| **25** | Cannabaceae | 0.3 | 119.8 | 99.0 | Clusiaceae | 0.5 | 97.0 | 96.7 | Olacaceae | 0.3 | 79.7 | 98.7 |
| **26** | Lauraceae | 0.3 | 120.0 | 99.2 | Thymelaeaceae | 0.5 | 97.4 | 97.1 | Clusiaceae | 0.2 | 79.9 | 99.0 |
| **27** | Ochnaceae | 0.3 | 120.3 | 99.4 | Oleaceae | 0.4 | 97.9 | 97.5 | Dilleniaceae | 0.2 | 80.1 | 99.3 |
| **28** | Melastomataceae | 0.2 | 120.5 | 99.6 | Melastomataceae | 0.4 | 98.3 | 97.9 | Primulaceae | 0.1 | 80.3 | 99.5 |
| **29** | Thymelaeaceae | 0.2 | 120.7 | 99.7 | Rubiaceae | 0.4 | 98.6 | 98.3 | Melastomataceae | 0.1 | 80.4 | 99.6 |
| **30** | Moraceae | 0.1 | 120.8 | 99.8 | Annonaceae | 0.4 | 99.0 | 98.7 | Ixonanthaceae | 0.1 | 80.5 | 99.7 |
| **31** | Oxalidaceae | 0.1 | 120.9 | 99.9 | Cannabaceae | 0.2 | 99.2 | 98.9 | Urticaceae | 0.1 | 80.5 | 99.8 |
| **32** | Phyllanthaceae | 0.0 | 120.9 | 100.0 | Primulaceae | 0.2 | 99.4 | 99.1 | Magnoliaceae | 0.0 | 80.6 | 99.8 |
| **33** | Primulaceae | 0.0 | 121.0 | 100.0 | Phyllanthaceae | 0.2 | 99.6 | 99.3 | Oleaceae | 0.0 | 80.6 | 99.9 |
| **34** | Putranjivaceae | 0.0 | 121.0 | 100.0 | Oxalidaceae | 0.2 | 99.7 | 99.4 | Ochnaceae | 0.0 | 80.6 | 99.9 |
| **35** | Achariaceae | 0.0 | 121.0 | 100.0 | Stemonuraceae | 0.1 | 99.9 | 99.6 | Hypericaceae | 0.0 | 80.7 | 100.0 |
| **36** | | | | | Dilleniaceae | 0.1 | 100.0 | 99.7 | Oxalidaceae | 0.0 | 80.7 | 100.0 |
| **37** | | | | | Ebenaceae | 0.1 | 100.1 | 99.8 | | | | |
| **38** | | | | | Apocynaceae | 0.1 | 100.1 | 99.8 | | | | |
| **39** | | | | | Elaeocarpaceae | 0.1 | 100.2 | 99.9 | | | | |
| **40** | | | | | Meliaceae | 0.0 | 100.2 | 99.9 | | | | |
| **41** | | | | | Symplocaceae | 0.0 | 100.3 | 99.9 | | | | |
| **42** | | | | | Cornaceae | 0.0 | 100.3 | 100.0 | | | | |
| **43** | | | | | Chrysobalanaceae | 0.0 | 100.3 | 100.0 | | | | |

# 3

# The imprint of logging on tropical forest carbon stocks: a Bornean case-study

*Litter is a minor component of C but might significantly influence total C balance in the forests. This picture shows forest litter in a Dipterocarp forest (Malinau, North Kalimantan)*

*(Picture by Andes Hamuraby Rozak)*

# Abstract

In tropical forests, selective logging generates a significant reduction of above-ground carbon stocks, due to direct removal of a few large merchantable individuals, and the death of smaller injured or smashed trees following harvesting. Several studies have shown a strong correlation between logging intensity and a reduction of biodiversity, wood production, and biomass stocks. However, little is known about the long-term effects of logging on the main forest carbon (C) stocks in above and below-ground tree biomass, deadwood, litter, and soil. In this study we quantified C stocks in 28 0.25-ha plots located in a mixed Dipterocarp forest, Borneo, Indonesia, logged 16 years ago at different intensities ranging from 0 to 57% of initial biomass removed. We investigated the effect of logging intensity, topography, and soil variables on each C stock using linear mixed models. Sixteen years after logging, total C stocks ranged from 218 to 554 Mg C ha$^{-1}$ with an average of 314 ± 21 Mg C ha$^{-1}$, of which more than 75% were found in live trees. Logging intensity was found to be the main factor explaining the variability in carbon stored in above- and below- ground biomass of tree DBH > 20 cm and deadwood. Simultaneously, the proportion of deadwood increased with logging intensity reaching 13.5% of total C stocks in intensively logged plots (> 20% removal of initial biomass). This study confirmed, therefore, the need to limit logging intensity to a threshold of 20% of initial biomass removal in order to limit the long-term accumulation of deadwood after logging, probably due to high post-logging mortality. With more than half of all Bornean forests already logged, accounting for total C post-logging is key to better assess the long-term carbon footprint of commercial logging in the region and is a necessary step towards the development of C-oriented forest management in the tropics.

**Keywords**: Above- and below-ground carbon; carbon stock; Dipterocarp forests; logged forest

## 3.1 Introduction

Bornean forests have mainly been exploited since the 1960s and with little concerns on ecological drawbacks and no implementation of appropriate logging and management practices (Nasi and Frost 2009; Nicholson 1979; Putz, Sist, et al. 2008). With increasing awareness on the fast degradation of Bornean forests, guidance to reduce the negative impacts of logging have been proposed since the 1990s, but remains poorly implemented in practice (Nasi and Frost 2009). In 2010, almost half of the Bornean forests had been affected by commercial timber extraction (Gaveau et al. 2014) and deforestation is still ramping up at high rate due to fast expansion of commercial plantations, such as oil palm (Margono et al. 2014). The remaining tropical forests, not only in Borneo, but all around the tropics, are under increasing anthropogenic pressure (Potapov et al. 2017) and logged forests are likely to play a key role in the future provision of ecosystem services, such as the production of wood, sequestration of carbon and maintenance of biodiversity (Edwards, Tobias, et al. 2014; Sist et al. 2015).

Even though reduced-impact logging techniques have been proposed and applied in the tropics (Miller et al. 2011; Putz, Sist, et al. 2008), poor implementation of these prescriptions still makes selective logging largely detrimental for tropical forest ecosystems. Widespread damages to residual stands and soils (Picard, Gourlet-Fleury, and Forni 2012; Pinard, Barker, and Tay 2000) induced long-lasting reduction of both biomass (Rutishauser et al. 2015) and timber (Vidal, West, and Putz 2016) stocks. Incidental damages are unavoidable, being directly related to logging intensity (Sist, Sheil, et al. 2003) and to the methods of tree felling and skidding (Pinard and Putz 1996; Sist and Nguyen-Thé 2002). Carbon (C) emissions induced by incidental damages, log wastes, and infrastructures can be up to 2-3 times higher than the C emissions related directly to extracted logs (Pearson, Brown, and Casarim 2014). Recent studies showed that commercial logging was found to be a major source of green-house gas emission, forming up to 50% of annual emissions related to forest degradation (Pearson et al. 2017).

While timber is generally exported, incidentally killed trees, along with logging residues, remain in the forest as deadwood and slash in the forest floor and can form up to 50% of total C stocks in logged forests (Osone et al. 2016; Pfeifer et al. 2015). By creating large canopy gaps, logging also affects the production of litter (Prasetyo et al. 2015). In logging gaps, the increased temperature on the forest floor was shown to enhance the decomposition of deadwood and litter (Zhang et al. 2008; Zhou et al. 2007). Further, increased availability of C in soil may accelerate the decomposition of deeper organic material in the soil where the micro-fauna is nutrient limited (Fontaine et al. 2004). This phenomenon is called priming effect (Fontaine, Mariotti, and Abbadie 2003) and may explain the sharp decrease of SOC observed 50 years after logging in a tropical logged African forest (Chiti et al. 2015).

Most C studies investigating the effects of logging in Bornean forests have focused on above-ground biomass (e.g. (Ioki et al. 2014; Kenzo et al. 2010; Morel et al. 2011) with a few exceptions also looking at other C pools (e.g. (Osone et al. 2016; Pfeifer et al. 2015; Saner et al.

2012). A better understanding of the distribution and variability of C stocks in logged forests is required to accurately estimate the carbon footprint of logging activities. The present study offers to quantify carbon stocks in five major pools, namely above and below-ground tree biomass, deadwood, litter, and organic carbon in soil at Malinau Research Forest, Borneo, Indonesia. Based on the hypothesis that logging has a significant influence on C stocks after 16 years, this study specifically aims to: a) estimate total C stocks and the proportion of each C pool along a gradient of logging intensity (ranging from 0 to 57% of initial biomass removed), and b) identify the factors influencing the variability in these C pools. Getting detailed estimates of C stocks post-logging and knowing the effect of logging intensity on total C stocks will help refine the carbon budget of managed forests and develop C-oriented forest management.

## 3.2 Materials and methods

### 3.2.1 Study site

Malinau Research Forest (MRF) was established in 1998/1999 with the aim to develop a sustainable forest management program that reduces logging-impacts and preserves the biodiversity along with the wellbeing of local communities (CIFOR and ITTO 2002; Gunarso et al. 2007; Sist, Sheil, et al. 2003). MRF is located in a logging concession owned by PT Inhutani II in Malinau, North Kalimantan (2°45'N, 116°30'E). The area is 100 to 300 m above sea level with 10-70% slope and an annual rainfall of around 3,790 mm. The forest is mainly composed of Dipterocarps, of which most species are prized commercial species, and stands among the most diverse Indonesian forests with 205 tree species inventoried (Sheil et al. 2010). MRF was selectively logged in 1999/2000 with different intensities, ranging from 3 to 13 trees harvested per hectare (Sist, Sheil, et al. 2003). The Indonesian selective logging and planting system (TPTI) allows all commercial trees with diameter at breast height (DBH) over 50 or 60 cm (depending on the forest type) to be harvested within a felling cycle of 35 years. In MRF, the targeted commercial tree species were *Agathis borneensis*, *Dipterocarpus* spp., and *Shorea* spp. (Sist, Sheil, et al. 2003).

### 3.2.2 Experimental design

Twenty-four 1-ha plots (100 m x 100 m) were randomly established in 1998/1999 before logging occurred (Sist, Sheil, et al. 2003). In each plot, all trees with a DBH >20 cm ($DBH_{>20}$) were mapped, tagged, and identified to the lowest taxonomic level. Trees were identified by a professional botanist in 1999/2000 and herbarium vouchers were deposited in Herbarium Bogoriense. A total of 6,696 trees were identified at species (85.1%), genus (10.7%), and family (4.2%) levels. Logging took place in 1999/2000. An overview of logging intensity and techniques used in MRF is given elsewhere (Sist, Sheil, et al. 2003). Before logging (1999), all trees $DBH_{>20}$ were systematically recorded, girth at breast height measured and crown forms and positions recorded. Tree status (live or dead), stem damages, and cause of death of all trees were recorded in all plots 8 months after logging (Sist, Sheil, et al. 2003). In 2015, 7 out of 24 1-ha plots were surveyed and diameter of all trees $DBH_{>20}$ was measured at 130 cm or 50 cm above any buttress or deformity. Additionally, in 2016, ten quadrats of 10 m x 10 m were randomly placed in each of those 7 plots to measure trees with DBH between 5 and 20 cm ($DBH_{5\text{-}20}$), deadwood, and litter. For 2015 and 2016 measurements, trees were identified by an experienced parabotanist at species (74.9%), genus (25%), and family (0.1%) levels. Tree girths were measured at 130 cm using a tape meter and converted into diameter, while total and trunk heights were measured using a laser rangefinder (Bushnell G-Force 1300 ARC). After data collection, a soil pit was dug in 2 quadrats chosen randomly in each plot (except in plot C09 where 3 pits were dug) leading to a total of 15 soil pits.

### 3.2.3 Logging intensity and C stocks

Logging intensity is defined as the ratio between the biomass lost at first post-logging measurement and pre-logging biomass stock (expressed as a percentage of pre-logging biomass). Biomass lost corresponds to the summed biomass of timber harvested and injured trees that died before the first post-logging census. Usually injured trees will die during the first 2 years after logging (Shenkin et al. 2015; Sist et al. 2014) and damages will be concentrated around gaps created by harvested trees (Pearson, Brown, and Casarim 2014). Logging intensity was estimated at 0.25-ha scale (each plot was divided into 4 subplots (50 m x 50 m) giving 28 subplots in total) to account for the large heterogeneity in logging treatment and damages within 1-ha plots. Logging intensity ranged from 0 to 57% of initial biomass lost (Table 4-2). Neither tree biomass, nor logging intensity was not found spatially correlated above 30 m (Figure 4-3 and Figure 4-4), avoiding pseudo-replication among subplots.

Five main C stocks were assessed as recommended by IPCC (2006), and quantified within each subplot: C stored in (i) live trees with a DBH between 5 and 20 cm, hereinafter $AGC_{5\text{-}20}$, and larger than 20 cm DBH ($AGC_{>20}$), (ii) coarse roots of trees DBH 5-20 and >20 cm (referred to as $BGC_{5\text{-}20}$ and $BGC_{>20}$, respectively), (iii) deadwood composed of coarse woody debris (CWD) having a diameter >10 cm and standing dead trees DBH >10 cm, (iv) litter, and (v) soil organic carbon in the top 1 m (SOC). Carbon stocks were calculated using a nested design: $AGC_{>20}$ and $BGC_{>20}$ were estimated across the whole 0.25-ha subplot, whereas $AGC_{5\text{-}20}$, $BGC_{5\text{-}20}$, deadwood, litter, and SOC were estimated in the 10 x 10 m quadrats and then averaged by subplot. For the sake of simplicity, a default ratio of 47% was used to estimate the carbon content of both live and dead biomass (IPCC 2006). Total C stocks correspond to the sum of all five C stocks at subplot level expressed in Mg C $ha^{-1}$.

*3.2.3.1 Above- and below ground biomass (AGB and BGB)*

AGB was estimated using a generic allometric model including DBH, wood density (ρ) and a climate index (E) (Chave et al. 2014). Such generic allometric models were shown to be more accurate and less biased than local models, notably in Dipterocarp forests (Rutishauser et al. 2013). Wood densities arise from the Global Wood Density Database (Chave et al. 2009; Zanne et al. 2009) using the lowest taxonomic level available. For species not present in the database, a wood density of $\rho = 0.58$ g $cm^{-3}$ were used. Root biomass ($BGB_{>20}$ and $BGB_{5\text{-}20}$) were estimated based on DBH using an allometric model developed in a mixed Dipterocarp forest (Niiyama et al. 2010). $AGB_{5\text{-}20}$, $AGB_{>20}$, $BGB_{5\text{-}20}$, and $BGB_{>20}$ were calculated using 2015 and 2016 data.

*3.2.3.2 Deadwood*

All fallen and standing deadwood with diameter >10 cm in each 100 $m^2$ quadrat were measured. For fallen deadwood, diameters at both ends and length (L) of each piece of deadwood lying in or crossing the quadrat were measured (Gove and Deusen 2011). For deadwood expanding outside the quadrat's boundaries, diameters were measured at the point of intersection with any boundary, and the piece wood length is the distance between these two points, representing the portion lying in the quadrat. The volume of each fallen deadwood ($V_f$) was calculated using conic-paraboloid formula (Fraver, Ringvall, and Jonsson 2007), as follows:

$$V_f = \frac{L_d}{12} \cdot (5 \cdot A_s + 5 \cdot A_l + 2 \cdot \sqrt{A_s \cdot A_l})$$

where L, $A_s$ and $A_l$ are the length (m) and the cross-sectional area ($m^2$) at the small- and large-end diameter of a deadwood, respectively. Deadwood mass is generally obtained by multiplying the volume of each piece by its respective wood density ($\rho_{DW}$, gr $cm^{-3}$). The volume of a standing deadwood was considered as a cylinder ($V_s$), of which height and DBH were measured and multiplied by a generic form factor (0.48) for broadleaved tree species (Cannell 1984). Deadwood density ($\rho_{DW}$, Table 4-3) was estimated visually using the three following decay classes (Walker et al. 2014):

Class 1 (Solid): little decay, extensive bark cover, leaves and fine twigs present, logs relatively undecayed.

Class 2 (Intermediate): No bark and few branch stubs (not moving when pulled), sapwood decaying

Class 3 (Rotten): Wood largely decayed, often scattered across the soil surface, logs elliptical in cross-section.

For each class, average dry wood density was determined by collecting 40 wood samples randomly for class 1, 2, and 3, respectively. Wood samples were weighed fresh in the field and oven-dried (at 80° C until constant weight) to compute dry weight per wet volume.

#### *3.2.3.3 Litter*

The litter layer is defined as all dead organic material on the top of the mineral soil (Walker et al. 2014). Dead material with diameter <10 cm is included in this layer. The litter sample was collected in a 1 m x 1 m subplot randomly chosen in each quadrat and weighed wet. A sub-sample (≤0.5 kg) was then dried until constant weight in the laboratory to estimate the dry weight. Dry mass of litter was calculated based on the wet-to-dry weight ratio of sub-samples.

#### *3.2.3.4 Soil Organic Carbon (SOC)*

Soil samples were collected volume based using metal rings of known volume (*c*. 92 $cm^3$) at five depth intervals (0-5, 5-15, 15-30, 30-50, and 50-100 cm) in each soil pit to determine chemical and physical properties. Soil bulk density (g $cm^{-3}$) and a fraction of gravel (%) for each depth were determined after sieving the dried soil using a 2-mm mesh. Organic carbon concentration (mg $g^{-1}$) of the sample was estimated using a wet oxidation method (Walkley and Black 1934). Other soil properties, such as texture, pH ($H_2O$), CEC, available phosphorus (Bray I/II), and nitrogen (Kjeldahl) were also determined. SOC stocks (Mg $ha^{-1}$) for each depth were calculated as the function of soil bulk density, carbon concentration, and coarse fragment for each depth (Batjes 1996). Total SOC stocks (Mg $ha^{-1}$) were then calculated as the sum of SOC stocks of each depth.

### 3.2.4 Data analyses

Linear mixed models were developed to test the relationship between logging intensity, topography (i.e. slope), and soil variables on each C stock (Y). The effect of logging intensity and topography on the different C pools were tested across all subplots (n = 28), while the effect of soil could be tested only in 15 subplots where a pit was dug. To avoid collinearity of the soil variables, only three soil variables (clay, nitrogen, and available phosphorus) were included in the model based on correlation with the first two axes of a Principal Component Analysis (see Supplementary Information). Initial forest structure within each plot was accounted for as random effect (u) to lower spatial correlation. $AGC_{>20}$, deadwood, total C stocks, logging intensity, and available phosphorus content were normalized by log-transformation to fulfill assumption of normality, and therefore to avoid heteroscedasticity of residuals. The initial linear mixed model for each C pool is therefore defined as follows:

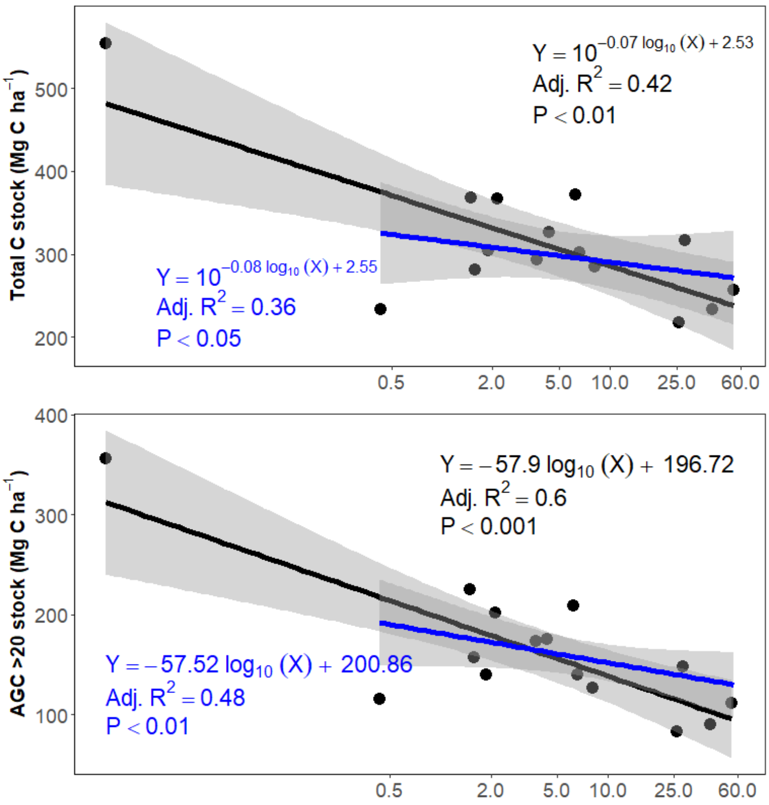
$$Y = \beta_0 + \beta_1 \cdot logging\ intensity + \beta_2 \cdot slope + \beta_3 \cdot clay + \beta_4 \cdot nitrogen + \beta_5 \cdot available\ phosphorus + u + \varepsilon_a$$

with $\varepsilon_a \sim N(0, \sigma_a^2)$ and β are the coefficients of the fixed effects tested. All analyses were carried on in R (R Core Team 2017). The *lmer* function in the 'lme4' package was used to fit linear mixed-effects models (Bates et al. 2015), the "MuMIn" package to estimate marginal (the proportion of variance explained by the fixed factors) and conditional (the proportion of variance explained by both fixed and random factors) $R^2$ of the model (Barton 2016), the "glmulti" package to predict the best fit model based on the lowest Bayesian Information Criterion (BIC) as well as to estimate the relative importance value for each variable used in the model (Calcagno and de Mazancourt 2010), the 'car' package to analyze significant difference between the predictor variables included in the model (Fox and Weisberg 2011), and the "PMCMR" package to analyze the difference between artificial logging intensity classes based on 0-33$^{rd}$ (0-2.1%), 34-66$^{th}$ (2.1-19%), and 67-100$^{th}$ (19-56.9%) percentiles of the logging intensity distribution using Kruskal-Wallis test followed by Dunn's test (Pohlert 2016).

## 3.3 Results

### 3.3.1 Total C stocks in a logged forest

Sixteen years after logging, total C stocks at MRF ranged from 218 to 554 Mg C ha$^{-1}$ (Figure 3-1) with an average of 314 ± 21 Mg C ha$^{-1}$, of which more than 75% were found in live trees DBH >5 cm (Figure 3-3B, Table 3-5). Total C stocks generally decreased when logging intensity increased (Figure 3-1, adj-$R^2$ = 0.42, slope = -0.07, $P$ <0.01), driven by the strong effect of logging intensity on $AGC_{>20}$ (Figure 3-1, adj-$R^2$ = 0.60, slope = -57.90, $P$ <0.01). Excluding 0% logging intensity, slope and adjusted $R^2$ of linear model were slightly changed without affecting the result (Figure 3-1, the solid blue line). No trend along gradient of logging intensity was found on $AGC_{5\text{-}20}$, $BGC_{5\text{-}20}$, SOC stock, and litter C stock (Figure 3-2, all $P$ >0.05). Areas affected by high logging intensity had in average 33% less $AGC_{>20}$ and $BGC_{>20}$ than unmanaged areas or logged at low intensity (Figure 3-3). Deadwood stocks were positively correlated with logging intensity (adj-$R^2$ = 0.36, slope = 0.35, $P$ <0.05), increasing significantly in areas with high logging intensity where it formed 13.5% of total C stock (Figure 3-3).



Total C stock (Mg C ha$^{-1}$)
$Y = 10^{-0.07\log_{10}(X) + 2.53}$
Adj. $R^2 = 0.42$
$P < 0.01$
$Y = 10^{-0.08\log_{10}(X) + 2.55}$
Adj. $R^2 = 0.36$
$P < 0.05$
500
400
300
200
0.5
2.0
5.0
10.0
25.0
60.0
AGC >20 stock (Mg C ha$^{-1}$)
$Y = -57.9\log_{10}(X) + 196.72$
Adj. $R^2 = 0.6$
$P < 0.001$
$Y = -57.52\log_{10}(X) + 200.86$
Adj. $R^2 = 0.48$
$P < 0.01$
400
300
200
100
0.5
2.0
5.0
10.0
25.0
60.0

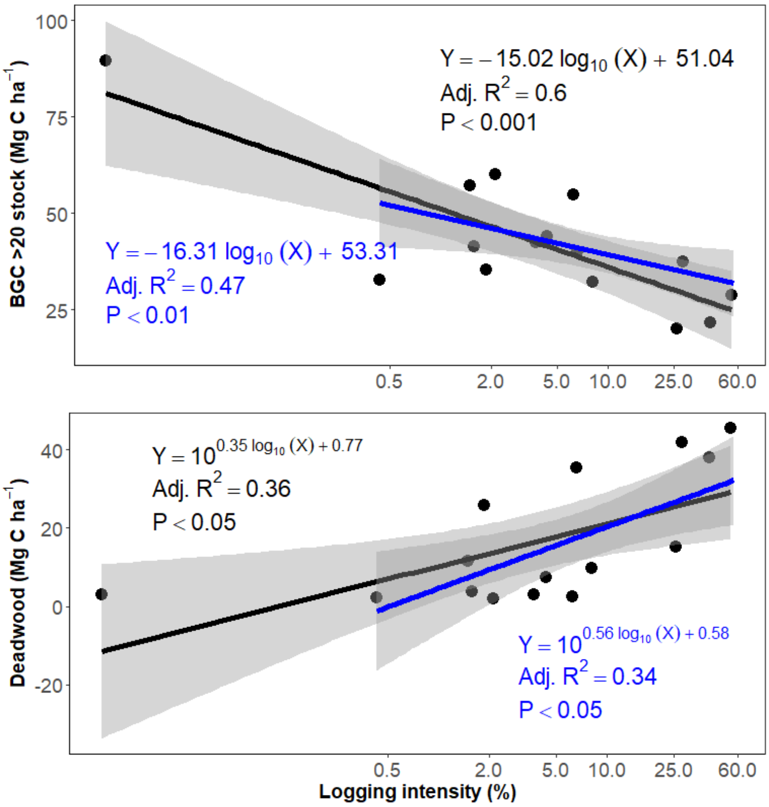



*Figure 3-1 Total C, $AGC_{>20}$, $BGC_{>20}$, and deadwood stocks along a gradient of logging intensity (n = 15 subplots, P <0.05). The solid black line is a linear model with 95% confidence interval. The solid blue line is a linear model excluding 0% logging intensity with 95% confidence interval.*

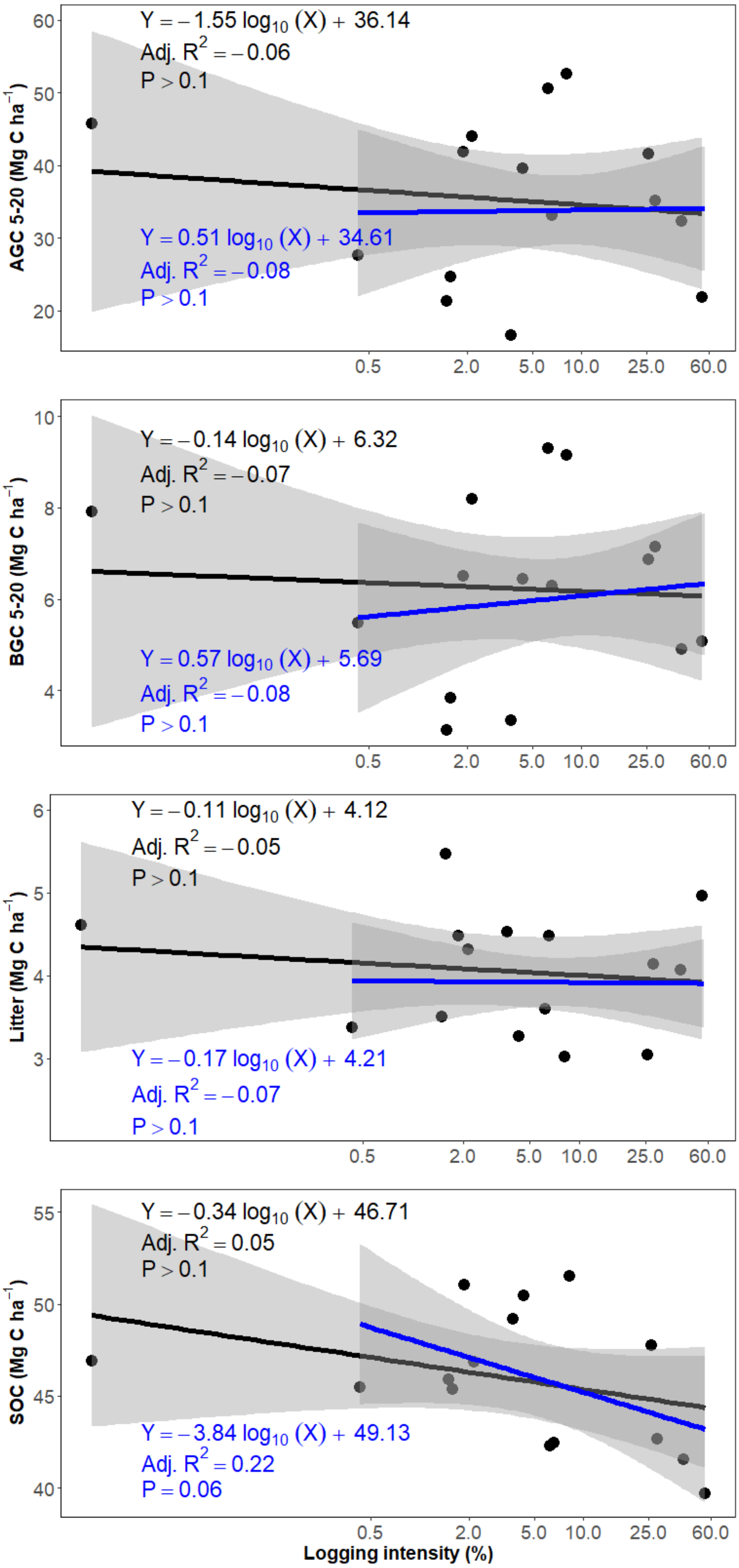



*Figure 3-2 $AGC_{5-20}$, $BGC_{5-20}$, litter and SOC stocks along a gradient of logging intensity (n = 15 subplots, P >0.05). The solid black line is a linear model with 95% confidence interval. The solid blue line is a linear model excluding 0% logging intensity with 95% confidence interval.*

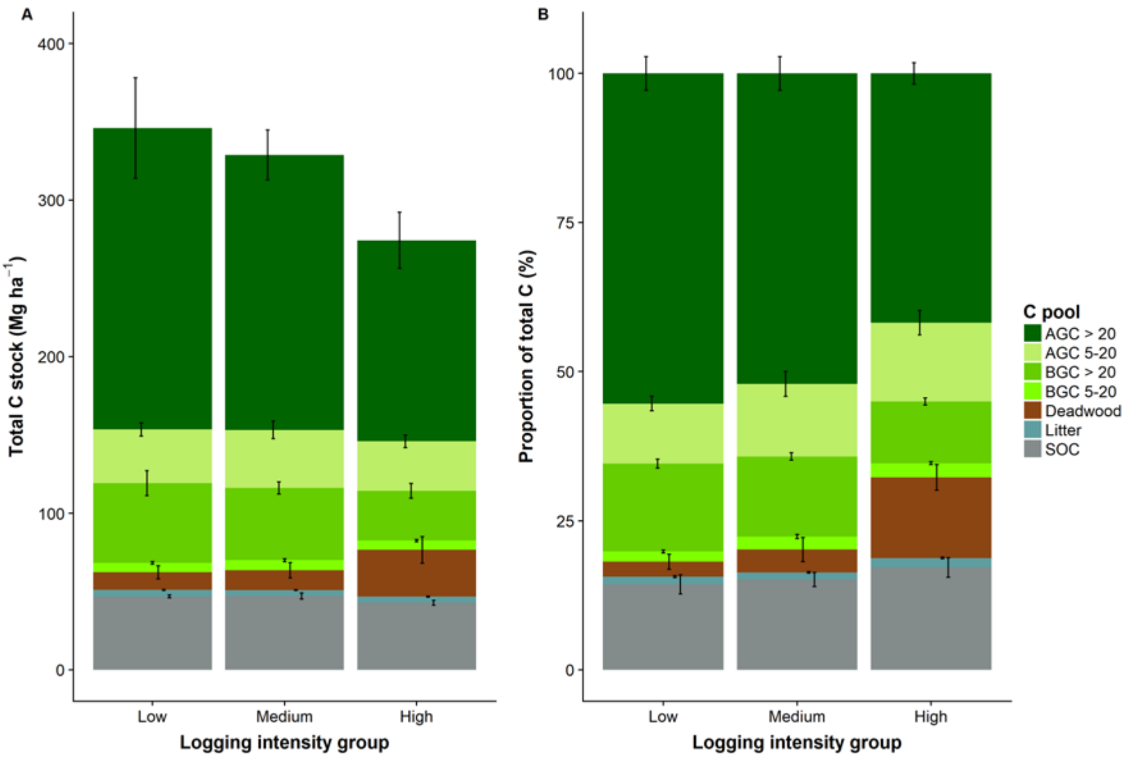



*Figure 3-3 Total C stocks (A) and its proportion (B) for each pool in different logging intensity group 16 years after logging. Logging intensity was grouped into 3 classes corresponding to 0-33rd (0-2.1%), 34-66th (2.1-19%), and 67-100th (19-57%) percentiles of the logging intensity distribution, respectively. The stocks and proportions of $AGC_{>20}$, $BGC_{>20}$, $AGC_{5-20}$, $BGC_{5-20}$, deadwood, and litter were averaged from 28 subplots, while SOC from 15 subplots. Error bars indicate one standard error of the mean.*

### 3.3.2 Drivers of C pools

The explanatory variables explained between 25 and 63% of the total variance among the C pools (Table 3-1, marginal $R^2$). Logging intensity was found to be the main driver explaining variation in $AGC_{>20}$, $BGC_{>20}$, deadwood, and total C stocks when initial forest structure and key environmental variables were included (Table 3-1). The influence of logging intensity on $AGC_{>20}$, $BGC_{>20}$, deadwood, and total C stocks was corroborated by high relative importance value (>65%, Table 3-8).

*Table 3-1 Goodness of fit (BIC, marginal and conditional $R^2$) of the best model, coefficients (β), standard error (SE), and p-values (significant values are in bold) of explanatory variables retained for each C pool. In all cases, logging intensity range between 0 and 55% of initial biomass removed (n = 15).*

| **C pools** | **BIC** | **Marginal $R^2$** | **Conditional $R^2$** | **Predictor** | **β** | **SE** | ***P*** |
|---|---|---|---|---|---|---|---|
| **$AGC_{>20}$** | 163.8 | 0.61 | 0.61 | Intercept | 196.7 | 12.14 | **<0.001** |
| | | | | Logging intensity | -57.9 | 11.4 | **<0.001** |
| **$BGC_{>20}$** | 123.3 | 0.63 | 0.65 | Intercept | 51.04 | 3.15 | **<0.001** |
| | | | | Logging intensity | -15.02 | 2.96 | **<0.001** |
| **Deadwood** | 24.5 | 0.38 | 0.41 | Intercept | 0.77 | 0.12 | **<0.001** |
| | | | | Logging intensity | 0.35 | 0.11 | **0.006** |
| **Litter** | 35.7 | 0.51 | 0.51 | Intercept | 5.64 | 0.84 | **<0.001** |
| | | | | Logging intensity | -0.25 | 0.14 | 0.095 |
| | | | | Slope | 0.03 | 0.01 | **0.034** |
| | | | | Clay | 0.09 | 0.02 | **0.003** |
| **SOC** | 84.1 | 0.25 | 0.46 | Intercept | 36.91 | 3.42 | **<0.001** |
| | | | | Nitrogen | 88.16 | 32.21 | 0.054 |
| **Total C** | -25.4 | 0.48 | 0.53 | Intercept | 2.53 | 0.02 | **<0.001** |
| | | | | Logging intensity | -0.07 | 0.02 | **0.003** |

## 3.4 Discussion

Our study aimed at investigating the effects of logging on C stocks in Dipterocarp logged forests. Focusing on the most significant C pools generally reported to form >80% of total C stored in tropical forests (Malhi et al. 2009), we found that total C stocks were significantly influenced by logging intensity 16 years after timber harvest and therefore confirms our hypothesis. The main result is the transfer from live biomass ($AGC_{>20}$ and $BGC_{>20}$) to the dead material. While dead neotropical trees have been reported to lose 90% of their mass within two decades (Hérault et al. 2010), deadwood stocks were about 3 times higher in intensively logged areas (>20% removal of initial biomass) than in low logging intensity areas (Figure 3-3A). Large logging wastes (e.g. forgotten logs) and large incidental killed trees might explain this difference 16 years after logging. Furthermore, another explanation lies in increased post-logging mortality of residuals trees in intensively logged stands. Mortality rates post-logging were shown to peak shortly after logging, and remain high after a decade compared to unlogged forests (Blanc et al. 2009; Sist et al. 2014). This reflects long-term effects of logging on forest ecosystems, and somehow lowered resilience with increasing logging intensity. A key challenge will be to know how long do these negative side effects last and how do they affect the ecosystem functioning. We found that several C pools can be relatively well predicted through the sole logging intensity, expressed as a percentage of initial biomass lost (Table 3-1). Unfortunately, information about logging intensity is usually unavailable in the field. With rapid development of remote sensing technique enabling to capture fine change in live biomass stocks (Coomes et al. 2017), a correlative approach using logging intensity as explanatory variable could provide an efficient surrogate to estimate total C stocks and other C pools (especially for $AGC_{>20}$ and $BGC_{>20}$, marginal $R^2$ >60%). Our results also corroborate the previous finding on the importance of deadwood in degraded forests (Pfeifer et al. 2015) and the need to account for other C pools when accurate calculations of C stocks and fluxes have to be done in human-modified tropical forests.

### 3.4.1 C stocks in logged forests and its driver

Sixteen years after logging, areas where high logging intensity occurred have lost around a third of their C stocks (Figure 3-3). Total C stocks in our study site were within the range of C stocks reported in secondary and primary Dipterocarp forests in Singapore (Ngo et al. 2013). The stocks of $AGC_{>20}$ in our site were also comparable with the same type of logged forests in Malaysian Borneo when the generic allometric model was used (Morel et al. 2011). The very high variation of total C stocks in MRF along the gradient of logging intensity (Figure 3-1) showed that logging intensity should be accounted for as explanatory variable rather than logged forests are seen as a whole ecosystem (Morel et al. 2011; Saner et al. 2012).

Most of the ecosystem C stocks was found in live tree biomass (77%), followed by SOC (15%) and deadwood (6%). Litter formed only a minor fraction (1.4%) (Table 3-5) and was only slightly affected by logging (Table 3-1). Logging shifts the ratio of live and dead materials after more than a decade, decreasing $AGC_{>20}$ by up to 14% and increasing deadwood stocks by 11% (Table 3-5). Thus, sustainable forest management should primarily focus on avoiding incidental damages through improving the ecological sustainability (Sist, Fimbel, et al. 2003), notably in preserving large trees (Sist et al. 2014).

Deadwood stock was correlated to logging intensity and was three times higher in highly logged than in lowly logged areas. However, the best model only captured 38% of the total variance (Table 3-1), revealing the large heterogeneity of deadwood stocks in logged forests. Average deadwood stock (18 ± 3 Mg C $ha^{-1}$) was in range with the result from a previous study (Pfeifer et al. 2015). However, comparing deadwood stock among forests is difficult because its stock depends on the amount of incidental damages (Pinard and Putz 1996; Sist and Nguyen-Thé 2002), environmental factors (Garbarino et al. 2015; Osone et al. 2016; Weedon et al. 2009), decomposition rates among species (Harmon et al. 1995; Hérault et al. 2010), and methodology used to assess deadwood volume (Fraver, Ringvall, and Jonsson 2007).

### 3.4.2 Implications for sustainable forest management

Our result revealed that logging's imprint is still largely perceptible after 16 years specifically on $AGC_{>20}$, $BGC_{>20}$, deadwood, and total C stocks (Table 3-1). Controlling logging intensity and combining it with silvicultural guidelines (Sist 2001; Sist, Picard, and Gourlet-Fleury 2003) are still relevant to minimize the impact of logging intensity to AGB and stand damage. More than half of C emissions from logging are related to logged trees forgotten in the field and incidentally killed trees (Griscom, Ellis, and Putz 2014). Strengthening and monitoring the adoption of reduced-impact logging (RIL) would help prevent logging damages and C emissions.

While 46% of Bornean forests were already logged in 2010 (Gaveau et al. 2014), these forests, if preserved, are likely to play an important role in the region for biodiversity conservation and providing other ecosystem services. Even though several studies have shown many benefits provided by logged forests (Bicknell et al. 2014; Meijaard and Sheil 2007), these forests are still disappearing due to illegal logging and forest conversion. Forest law enforcement, such as EU support for Indonesian government in accordance with Forest Law Enforcement Governance and Trade (FLEGT) policy (Schmitz 2016), was created to promote sustainable timber extraction.

Forests at Malinau are among the most diverse of Indonesia (Sheil et al. 2010) and our results revealed that they also harbor high C stocks. While biodiversity and C stocks seem only poorly related at the global scale (Sullivan et al. 2017), our study site combines both, as for some African forest sites (Day et al. 2014). Furthermore, the inclusion of carbon enhancement into forest management and REDD+ strategies remain to be done, either as interventions aimed at reducing emissions, or as parts of REDD+ investment frameworks (Hein and van der Meer 2012).

## 3.5 Conclusions

Total C stocks in unmanaged forests or logged at low intensity were on average higher than those found in areas with high logging intensity. Simultaneously, the proportion of deadwood was multiplied by 5 to reach 13.5% of total C in heavily logged areas. While C pool responded differently to logging and a few key environmental variables, logging intensity solely was found to be the main factor explaining the variability in $AGC_{>20}$, $BGC_{>20}$, deadwood, and total C stocks. Living trees remain the main C pool 16 years after logging, followed by a significant amount of C in deadwood and SOC. As logging intensity affect C pools in our site, it will have consequences for C stocks in the future. Considering that 32% of 114.1 million ha of permanent forest estate are designated as permanent production forest in Indonesia (Blaser et al. 2011), narrowing down C stock estimates in logged forests will be an important step for the Indonesian National Carbon Accounting System (The Ministry of Environment and Forestry 2013). Our findings, therefore, shed new light on the long-term imprint of logging on the carbon cycle in production forests of Indonesia and confirmed the need to limit logging intensity to a threshold of 20% of initial biomass removal in order to limit the long-term accumulation of deadwood after logging, probably due to high post-logging mortality.

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## Supplementary Table

*Table 3-2 Pre-logging forest structure and logging intensity at 0.25-ha subplot scale: number of pre-logging stem (tree), pre-logging basal area ($m^2$) pre-logging biomass (Mg), number of tree harvested (tree), tree biomass harvested (Mg), number of tree killed (tree), tree biomass killed (Mg) due to logging, and logging intensity (%) in 0.25-ha subplot level.*

| Plot | Subplot | Number of stems | Basal area | Pre-logging biomass | Number of trees harvested | Biomass harvested | Number of trees killed | Biomass killed | Logging intensity |
|---|---|---|---|---|---|---|---|---|---|
| **MRF-C12** | MRF-C12-1 | 66 | 7.22 | 81.75 | 0 | 0.00 | 1 | 3.06 | 3.75 |
| | MRF-C12-2 | 82 | 11.65 | 134.46 | 0 | 0.00 | 0 | 0.00 | 0 |
| | MRF-C12-3 | 62 | 8.23 | 104.75 | 0 | 0.00 | 1 | 3.86 | 3.69 |
| | MRF-C12-4 | 75 | 10.95 | 121.83 | 0 | 0.00 | 1 | 2.59 | 2.12 |
| **MRF-R12** | MRF-R12-1 | 57 | 6.27 | 68.56 | 0 | 0.00 | 1 | 0.29 | 0.42 |
| | MRF-R12-2 | 55 | 8.84 | 118.36 | 0 | 0.00 | 0 | 0.00 | 0 |
| | MRF-R12-3 | 82 | 12.34 | 165.49 | 0 | 0.00 | 0 | 0.00 | 0 |
| | MRF-R12-4 | 74 | 8.38 | 103.62 | 0 | 0.00 | 0 | 0.00 | 0 |
| **MRF-R01** | MRF-R01-1 | 54 | 7.18 | 83.25 | 0 | 0.00 | 1 | 1.55 | 1.87 |
| | MRF-R01-2 | 93 | 10.61 | 116.10 | 1 | 1.72 | 0 | 0.00 | 1.48 |
| | MRF-R01-3 | 45 | 4.54 | 46.37 | 0 | 0.00 | 0 | 0.00 | 0 |
| | MRF-R01-4 | 79 | 10.24 | 121.25 | 2 | 7.56 | 11 | 7.85 | 9.71 |
| **MRF-R02** | MRF-R02-1 | 65 | 6.73 | 72.99 | 2 | 9.53 | 1 | 0.51 | 8.14 |
| | MRF-R02-2 | 49 | 6.50 | 68.30 | 0 | 0.00 | 1 | 1.51 | 2.21 |
| | MRF-R02-3 | 80 | 6.66 | 70.96 | 0 | 0.00 | 10 | 3.44 | 4.33 |
| | MRF-R02-4 | 69 | 7.28 | 82.14 | 2 | 6.35 | 14 | 15.44 | 25.90 |
| **MRF-R06** | MRF-R06-1 | 56 | 7.71 | 101.69 | 1 | 20.10 | 3 | 1.61 | 21.35 |
| | MRF-R06-2 | 46 | 4.28 | 47.15 | 1 | 3.74 | 9 | 8.42 | 25.80 |
| | MRF-R06-3 | 76 | 9.50 | 111.56 | 3 | 10.47 | 31 | 52.59 | 56.86 |
| | MRF-R06-4 | 62 | 7.89 | 84.89 | 2 | 5.37 | 6 | 3.20 | 6.57 |
| **MRF-R07** | MRF-R07-1 | 60 | 7.80 | 99.59 | 4 | 32.24 | 12 | 9.16 | 40.87 |
| | MRF-R07-2 | 61 | 6.25 | 63.08 | 0 | 0.00 | 1 | 0.99 | 1.57 |
| | MRF-R07-3 | 78 | 8.09 | 95.47 | 2 | 18.76 | 19 | 11.23 | 31.41 |
| | MRF-R07-4 | 78 | 9.57 | 114.58 | 1 | 6.76 | 1 | 0.51 | 5.90 |
| **MRF-C09** | MRF-C09-1 | 75 | 13.64 | 182.31 | 5 | 36.34 | 19 | 18.57 | 28.15 |
| | MRF-C09-2 | 55 | 7.90 | 98.21 | 0 | 0.00 | 13 | 7.05 | 6.22 |
| | MRF-C09-3 | 83 | 11.30 | 117.99 | 5 | 36.08 | 31 | 30.95 | 54.83 |
| | MRF-C09-4 | 85 | 9.28 | 107.01 | 0 | 0.00 | 26 | 23.64 | 19.02 |

*Table 3-3 Decay classes and corresponding wood density (± standard error). Letters figure out significant difference among classes at P <0.05.*

| Decay class | Description | Average deadwood density (g cm$^{-3}$) |
|---|---|---|
| **1** | Little decay, bark cover extensive, leaves and fine twigs present, logs relatively undecayed. | 0.537 ± 0.025$^{a}$ |
| **2** | No bark and few branch stubs (not moving when pulled), sapwood decaying | 0.377 ± 0.010$^{b}$ |
| **3** | Wood often scattered across the soil surface, logs elliptical in cross-section. | 0.291 ± 0.010$^{c}$ |

*Table 3-4 The average (± standard error) of C stocks (Mg C ha$^{-1}$) by C pools and logging intensity group. Logging intensity was grouped into 3 classes corresponding to 0-33$^{rd}$, 34-66$^{th}$, and 67-100$^{th}$ percentiles of the logging intensity distribution, respectively. Letters figure out significant differences at P <0.05 after pairwise comparisons using Dunn's test.*

| C pool | Number of subplots | Logging intensity | | | Average |
|---|---|---|---|---|---|
| | | Low (0-2.1%) | Medium (2.1-19%) | High (19-56.9%) | |
| **AGC$_{>20}$** | 28 | 192.5 (24.9) $^{a}$ | 175.5 (11.9) a | 128.3 (13.3) $^{b}$ | 166.4 (11.5) |
| **BGC$_{>20}$** | 28 | 50.9 (6.2) $^{a}$ | 46.1 (2.9) $^{a}$ | 31.8 (3.5) $^{b}$ | 43.2 (3) |
| **AGC$_{5\text{-}20}$** | 28 | 34.3 (3.3) $^{a}$ | 37.2 (4.2) $^{a}$ | 31.6 (3) $^{a}$ | 34.4 (2) |
| **BGC$_{5\text{-}20}$** | 28 | 6.1 (0.6) $^{a}$ | 6.5 (0.8) $^{a}$ | 5.9 (0.6) $^{a}$ | 6.2 (0.4) |
| **Deadwood** | 28 | 11.2 (3.3) $^{a}$ | 12.6 (3.7) $^{a}$ | 29.8 (6.3) $^{b}$ | 17.7 (3) |
| **Litter** | 28 | 4.2 (0.2) $^{a}$ | 3.8 (0.2) $^{a}$ | 3.9 (0.2) $^{a}$ | 4 (0.1) |
| **SOC** | 15 | 46.9 (0.8) $^{a}$ | 47.2 (1.8) $^{a}$ | 42.9 (1.5) $^{a}$ | 45.9 (0.9) |
| **Total C** | 15 | 351.3 (42.3) $^{a}$ | 315.8 (14.3) $^{a}$ | 256.2 (19.6) $^{b}$ | 314.1 (21.3) |

*Table 3-5 The average (± standard error) of proportion C pools by total C stocks (%) for each logging intensity group. Logging intensity was grouped into 3 classes corresponding to 0-33$^{rd}$, 34-66$^{th}$, and 67-100$^{th}$ percentiles of the logging intensity distribution, respectively. Letters figure out significant differences at P <0.05 after pairwise comparisons using Dunn's test.*

| C pool | Logging intensity group | | | Average |
|---|---|---|---|---|
| | Low (0-2.1%) | Medium (2.1-19%) | High (19-56.8%) | |
| **AGC$_{>20}$** | 55.3 (2.6) $^{a}$ | 52 (2.6) $^{ab}$ | 41.8 (1.8) $^{b}$ | 50.6 (1.5) |

| | | | | |
|---|---|---|---|---|
| **$BGC_{>20}$** | 14.7 (0.7) [a] | 13.4 (0.6) [ab] | 10.4 (0.6) [b] | 13.1 (0.4) |
| **$AGC_{5-20}$** | 10.1 (1.1) [a] | 12.2 (1.9) [a] | 13.1 (2) [a] | 11.6 (0.7) |
| **$BGC_{5-20}$** | 1.7 (0.2) [a] | 2.2 (0.3) [a] | 2.4 (0.2) [a] | 2.1 (0.1) |
| **Deadwood** | 2.5 (1.2) [a] | 3.8 (1.8) [a] | 13.5 (2.1) [b] | 5.9 (1.2) |
| **Litter** | 1.3 (0.2) [a] | 1.2 (0.1) [a] | 1.6 (0.1) [a] | 1.4 (0.1) |
| **SOC** | 14.4 (1.5) [a] | 15.1 (1.1) [a] | 17.2 (1.6) [a] | 15.4 (0.9) |

*Table 3-6 Model fit statistics for mixed-effect models of C pools included logging intensity, mean slope, clay content, phosphorus content, and nitrogen content as fixed effects and plot as a random effect. Bold number on* p-value *shows significant variables (P < 0.05).*

| C pools | BIC | Marginal $R^2$ | Conditional $R^2$ | Predictor | β | SE | *P* |
|---|---|---|---|---|---|---|---|
| **$AGC_{>20}$** | -7.2 | 0.701 | 0.985 | Intercept | 1.69 | 0.28 | **<0.001** |
| | | | | Logging intensity | -0.20 | 0.06 | **0.006** |
| | | | | Slope | -0.00 | 0.00 | 0.659 |
| | | | | Clay | 0.01 | 0.01 | **0.047** |
| | | | | Phosphorus | -0.06 | 0.17 | 0.707 |
| | | | | Nitrogen | 3.18 | 2.19 | 0.173 |
| **$BGC_{>20}$** | 133.7 | 0.660 | 0.660 | Intercept | 34.52 | 30.61 | 0.277 |
| | | | | Logging intensity | -13.31 | 4.83 | **0.015** |
| | | | | Slope | 0.08 | 0.29 | 0.796 |
| | | | | Clay | 0.02 | 0.61 | 0.979 |
| | | | | Phosphorus | 2.61 | 21.78 | 0.906 |
| | | | | Nitrogen | 103.05 | 190.23 | 0.596 |
| **$AGC_{5-20}$** | 133.2 | 0.145 | 0.145 | Intercept | 14.04 | 30.18 | 0.648 |
| | | | | Logging intensity | -0.81 | 4.76 | 0.867 |
| | | | | Slope | 0.06 | 0.29 | 0.826 |
| | | | | Clay | 0.68 | 0.60 | 0.273 |
| | | | | Phosphorus | -4.37 | 21.47 | 0.841 |
| | | | | Nitrogen | 34.45 | 187.51 | 0.857 |
| **$BGC_{5-20}$** | 80.5 | 0.176 | 0.176 | Intercept | 1.47 | 5.21 | 0.781 |
| | | | | Logging intensity | -0.47 | 0.82 | 0.574 |
| | | | | Slope | 0.03 | 0.05 | 0.553 |
| | | | | Clay | 0.16 | 0.10 | 0.143 |
| | | | | Phosphorus | 1.31 | 3.71 | 0.728 |
| | | | | Nitrogen | -14.03 | 32.36 | 0.671 |
| **Deadwood** | 26.8 | 0.559 | 0.990 | Intercept | -5.41 | 0.79 | **<0.001** |
| | | | | Logging intensity | -0.71 | 0.18 | **0.002** |
| | | | | Slope | -0.03 | 0.00 | **0.000** |
| | | | | Clay | 0.09 | 0.01 | **0.000** |
| | | | | Phosphorus | 0.49 | 0.46 | 0.314 |
| | | | | Nitrogen | 18.80 | 6.17 | **0.012** |
| **Litter** | 40.6 | 0.602 | 0.602 | Intercept | 6.37 | 1.38 | **<0.000** |
| | | | | Logging intensity | 0.35 | 0.22 | 0.129 |
| | | | | Slope | 0.03 | 0.01 | **0.030** |
| | | | | Clay | -0.09 | 0.03 | **0.005** |
| | | | | Phosphorus | 0.19 | 0.98 | 0.846 |
| | | | | Nitrogen | 5.09 | 8.55 | 0.561 |
| **SOC** | 91.8 | 0.519 | 0.519 | Intercept | 28.55 | 7.57 | **0.002** |
| | | | | Logging intensity | -1.13 | 1.19 | 0.360 |
| | | | | Slope | -0.08 | 0.07 | 0.279 |
| | | | | Clay | 0.08 | 0.15 | 0.603 |
| | | | | Phosphorus | 3.40 | 5.39 | 0.538 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | | Nitrogen | 138.84 | 47.05 | **0.009** |
| **Total C** | 183.0 | 0.583 | 0.583 | Intercept | 233.72 | 158.60 | 0.161 |
| | | | | Logging intensity | -63.90 | 25.03 | **0.022** |
| | | | | Slope | -1.04 | 1.50 | 0.500 |
| | | | | Clay | 1.73 | 3.14 | 0.590 |
| | | | | Phosphorus | 13.63 | 112.85 | 0.906 |
| | | | | Nitrogen | 224.45 | 985.51 | 0.822 |

*Table 3-7 The most three parsimonious models for each C pool explaining the variability of C stocks in MRF ranked according to increasing of BIC.*

| No | Model | Marginal $R^2$ | Conditional $R^2$ | BIC |
|---|---|---|---|---|
| **$AGC_{>20}$** | | | | |
| **1** | $AGC_{>20}$~ logging intensity | 0.61 | 0.61 | 163.8 |
| **2** | $AGC_{>20}$~ logging intensity + nitrogen | 0.64 | 0.70 | 166.2 |
| **3** | $AGC_{>20}$~ logging intensity + slope | 0.60 | 0.60 | 166.4 |
| **$BGC_{>20}$** | | | | |
| **1** | $BGC_{>20}$~ logging intensity | 0.63 | 0.65 | 123.3 |
| **2** | $BGC_{>20}$~ logging intensity + nitrogen | 0.65 | 0.73 | 125.6 |
| **3** | $BGC_{>20}$~ logging intensity + phosphorus | 0.60 | 0.60 | 125.9 |
| **$AGC_{5-20}$** | | | | |
| **1** | $AGC_{5-20}$ ~ 1 | 0 | 0 | 121.9 |
| **2** | $AGC_{5-20}$ ~ clay | 0.11 | 0.11 | 122.7 |
| **3** | $AGC_{5-20}$ ~ phosphorus | 0.03 | 0.03 | 124.1 |
| **$BGC_{5-20}$** | | | | |
| **1** | $BGC_{5-20}$ ~ 1 | 0 | 0 | 69.7 |
| **2** | $BGC_{5-20}$ ~ clay | 0.12 | 0.12 | 70.3 |
| **3** | $BGC_{5-20}$ ~ phosphorus | 0.01 | 0.01 | 72.2 |
| **Deadwood** | | | | |
| **1** | Deadwood ~ logging intensity | 0.38 | 0.41 | 24.5 |
| **2** | Deadwood ~ logging intensity + clay | 0.44 | 0.51 | 24.8 |
| **3** | Deadwood ~ nitrogen | 0.35 | 0.35 | 25.2 |
| **Litter** | | | | |
| **1** | Litter ~ logging intensity + slope + clay | 0.51 | 0.51 | 35.7 |
| **2** | Litter ~ clay | 0.36 | 0.36 | 35.8 |
| **3** | Litter ~ slope + clay | 0.44 | 0.44 | 35.9 |
| **SOC** | | | | |
| **1** | SOC ~ nitrogen | 0.25 | 0.46 | 84.1 |
| **2** | SOC ~ 1 | 0 | 0.60 | 85.0 |
| **3** | SOC ~ slope + nitrogen | 0.30 | 0.48 | 85.4 |
| **Total C stocks** | | | | |
| **1** | C stocks ~ logging intensity | 0.48 | 0.53 | -25.4 |
| **2** | C stocks ~ logging intensity + clay + phosporus + nitrogen | 0.62 | 0.99 | -24.2 |
| **3** | C stocks ~ logging intensity + slope | 0.44 | 0.44 | -23.1 |

*Table 3-8 The relative importance value (%) of logging intensity, mean slope, clay, nitrogen, and available phosphorus content in the soil for each C stock. In all cases, logging intensity range between 0 and 55% of initial biomass removed (n = 15).*

| Stock | Fixed factor | Estimate | Unconditional variance | Number of models | Importance value (%) | +/- (alpha=0.05) |
|---|---|---|---|---|---|---|
| **AGC>20** | Intercept | 171.99 | 3624.74 | 32 | 100 | 118.02 |
| | Logging Intensity | -54.43 | 227.08 | 16 | 96 | 29.54 |
| | Nitrogen | 169.62 | 134575.85 | 16 | 26 | 719.09 |
| | Slope | 0.10 | 0.12 | 16 | 22 | 0.67 |
| | Available Phosphorus | 2.06 | 368.84 | 16 | 22 | 37.65 |
| | Clay | 0.01 | 0.21 | 16 | 21 | 0.89 |
| **BGC>20** | Intercept | 44.56 | 248.80 | 32 | 100 | 30.92 |
| | Logging Intensity | -14.01 | 15.58 | 16 | 96 | 7.74 |
| | Nitrogen | 46.60 | 9541.16 | 16 | 27 | 191.47 |
| | Available Phosphorus | 0.72 | 25.08 | 16 | 22 | 9.82 |
| | Slope | 0.02 | 0.01 | 16 | 21 | 0.15 |
| | Clay | 0.00 | 0.01 | 16 | 21 | 0.23 |
| **Deadwood** | Intercept | 0.61 | 1.62 | 32 | 100 | 2.50 |
| | Logging Intensity | 0.22 | 0.04 | 16 | 67 | 0.38 |
| | Nitrogen | -4.20 | 47.54 | 16 | 50 | 13.52 |
| | Clay | 0.02 | 0.00 | 16 | 49 | 0.05 |
| | Slope | 0.01 | 0.00 | 16 | 36 | 0.02 |
| | Available Phosphorus | -0.09 | 0.12 | 16 | 31 | 0.68 |
| **Litter** | Intercept | 5.78 | 1.98 | 32 | 100 | 2.76 |
| | Clay | -0.08 | 0.00 | 16 | 89 | 0.07 |
| | Slope | 0.02 | 0.00 | 16 | 61 | 0.04 |
| | Logging Intensity | -0.11 | 0.02 | 16 | 42 | 0.31 |
| | Nitrogen | 0.17 | 5.54 | 16 | 25 | 4.61 |
| | Available Phosphorus | -0.04 | 0.01 | 16 | 23 | 0.60 |
| **SOC** | Intercept | 39.32 | 70.32 | 32 | 100 | 16.44 |
| | Nitrogen | 64.64 | 3416.70 | 16 | 62 | 114.58 |
| | Slope | 0.03 | 0.00 | 16 | 32 | 0.09 |
| | Logging Intensity | 0.11 | 0.28 | 16 | 29 | 1.03 |
| | Clay | -0.01 | 0.01 | 16 | 28 | 0.15 |
| | Available Phosphorus | -0.61 | 3.23 | 16 | 24 | 3.52 |
| **Total C** | Intercept | 2.34 | 0.06 | 32 | 100 | 0.46 |
| | Logging Intensity | -0.07 | 0.00 | 16 | 85 | 0.08 |
| | Nitrogen | 0.95 | 1.76 | 16 | 46 | 2.60 |
| | Clay | 0.00 | 0.00 | 16 | 35 | 0.01 |
| | Available | -0.01 | 0.00 | 16 | 35 | 0.10 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Phosphorus | | | | | |
| | Slope | 0.00 | 0.00 | 16 | 24 | 0.00 |

*Table 3-9 The relative importance value (%) of logging intensity, mean slope, clay, nitrogen, and available phosphorus content in the soil for each C stock. Logging intensity range between 1.5 and 55% of initial biomass removed (excluding 0% of logging intensity, n = 13).*

| Stock | Fixed factor | Estimate | Unconditional variance | Number of models | Importance value (%) | +/- (alpha=0.05) |
|---|---|---|---|---|---|---|
| **$AGC_{>20}$** | Intercept | 232.41 | 3615.98 | 32 | 100 | 117.87 |
| | Logging Intensity | -64.29 | 312.10 | 16 | 97 | 34.63 |
| | Slope | -1.13 | 0.80 | 16 | 70 | 1.75 |
| | Clay | 0.44 | 0.80 | 16 | 29 | 1.75 |
| | Nitrogen | -62.76 | 57126.67 | 16 | 26 | 468.51 |
| | Available Phosphorus | 7.39 | 390.52 | 16 | 25 | 38.74 |
| **$BGC_{>20}$** | Intercept | 54.74 | 488.71 | 32 | 100 | 43.33 |
| | Logging Intensity | -25.92 | 74.66 | 16 | 98 | 16.94 |
| | Slope | -0.37 | 0.05 | 16 | 79 | 0.45 |
| | Clay | 0.85 | 0.60 | 16 | 63 | 1.52 |
| | Available phosphorus | 13.66 | 288.77 | 16 | 52 | 33.31 |
| | Nitrogen | -146.70 | 44412.56 | 16 | 49 | 413.10 |
| **Deadwood** | Intercept | 0.57 | 0.70 | 32 | 100 | 1.64 |
| | Logging Intensity | 0.49 | 0.05 | 16 | 88 | 0.44 |
| | Clay | 0.01 | 0.00 | 16 | 40 | 0.03 |
| | Available Phosphorus | -0.18 | 0.16 | 16 | 31 | 0.78 |
| | Nitrogen | -2.05 | 15.58 | 16 | 31 | 7.74 |
| | Slope | 0.00 | 0.00 | 16 | 27 | 0.01 |
| **Litter** | Intercept | 6.11 | 1.67 | 32 | 100 | 2.53 |
| | Clay | -0.09 | 0.00 | 16 | 93 | 0.06 |
| | Slope | 0.01 | 0.00 | 16 | 55 | 0.03 |
| | Logging Intensity | -0.02 | 0.01 | 16 | 24 | 0.17 |
| | Available Phosphorus | -0.07 | 0.10 | 16 | 24 | 0.62 |
| | Nitrogen | -0.37 | 4.36 | 16 | 22 | 4.10 |
| **SOC** | Intercept | 34.58 | 63.22 | 32 | 100 | 15.59 |
| | Nitrogen | 100.22 | 3193.89 | 16 | 80 | 110.78 |
| | Slope | 0.05 | 0.00 | 16 | 43 | 0.13 |
| | Clay | 0.02 | 0.01 | 16 | 31 | 0.16 |
| | Available Phosphorus | -0.91 | 4.81 | 16 | 26 | 4.30 |
| | Logging Intensity | -0.22 | 0.45 | 16 | 26 | 1.31 |
| **Total C** | Intercept | 2.44 | 0.02 | 32 | 100 | 0.30 |
| | Logging Intensity | -0.14 | 0.00 | 16 | 97 | 0.07 |
| | Clay | 0.01 | 0.00 | 16 | 75 | 0.01 |
| | Slope | 0.00 | 0.00 | 16 | 69 | 0.00 |
| | Available Phosphorus | 0.03 | 0.00 | 16 | 34 | 0.10 |
| | Nitrogen | -0.14 | 0.29 | 16 | 29 | 1.06 |

# Supplementary Figure

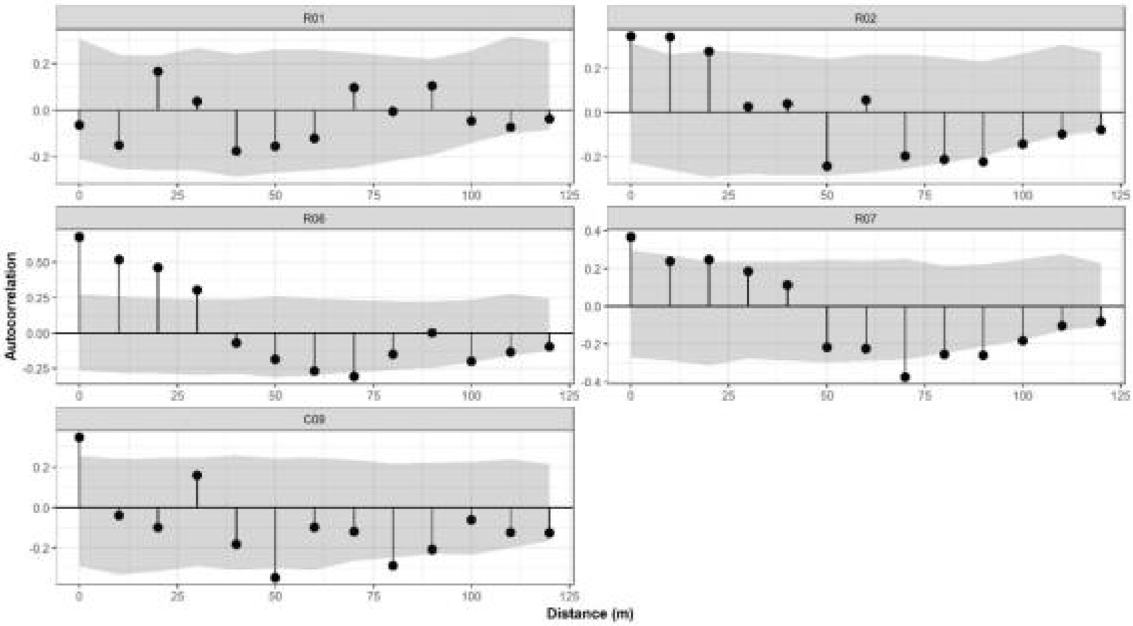


*Figure 3-4 Spatial autocorrelation of logging intensity for each plot. In plot R06, there was a quite strong autocorrelation for the first 30 m distance class as the values were larger than expected the null hypothesis of no autocorrelation (95% CI). After 30 m, logging intensity appears to be independent.*

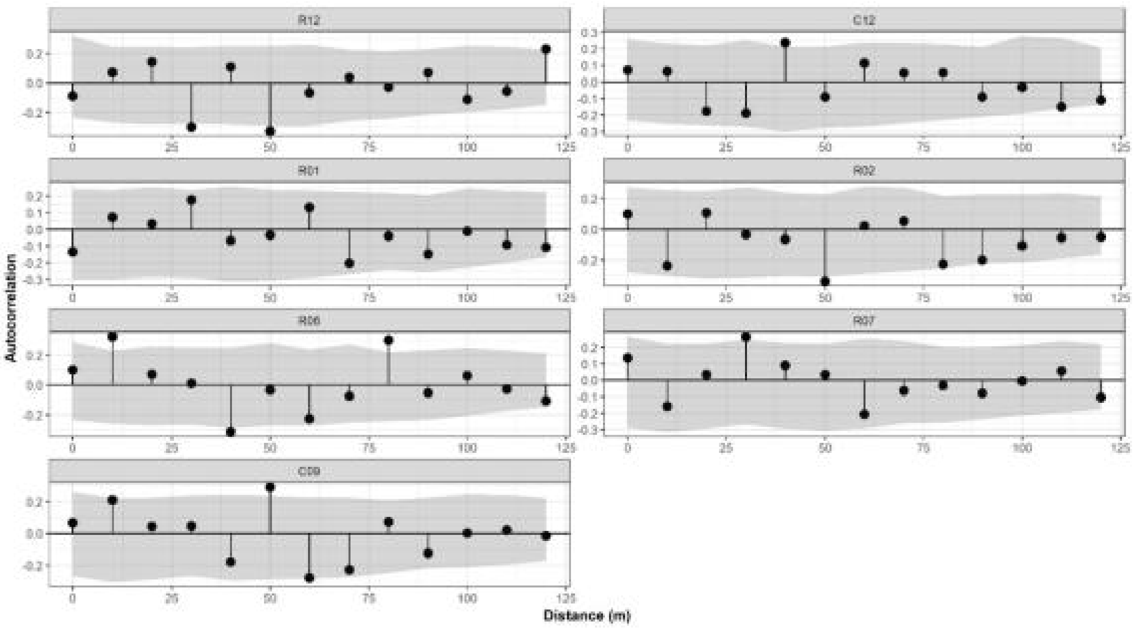


*Figure 3-5 Spatial autocorrelation of above-ground tree biomass for each plot. Grey areas show 95% CI.*

## Supplementary Information

Principal Component Analysis for soil variables

Deciding the most important soil variable for the linear mixed models using PCA.

Two-third of the variance contained in the data are retained by the first two principal components (Table 4-10, Figure 4-5).

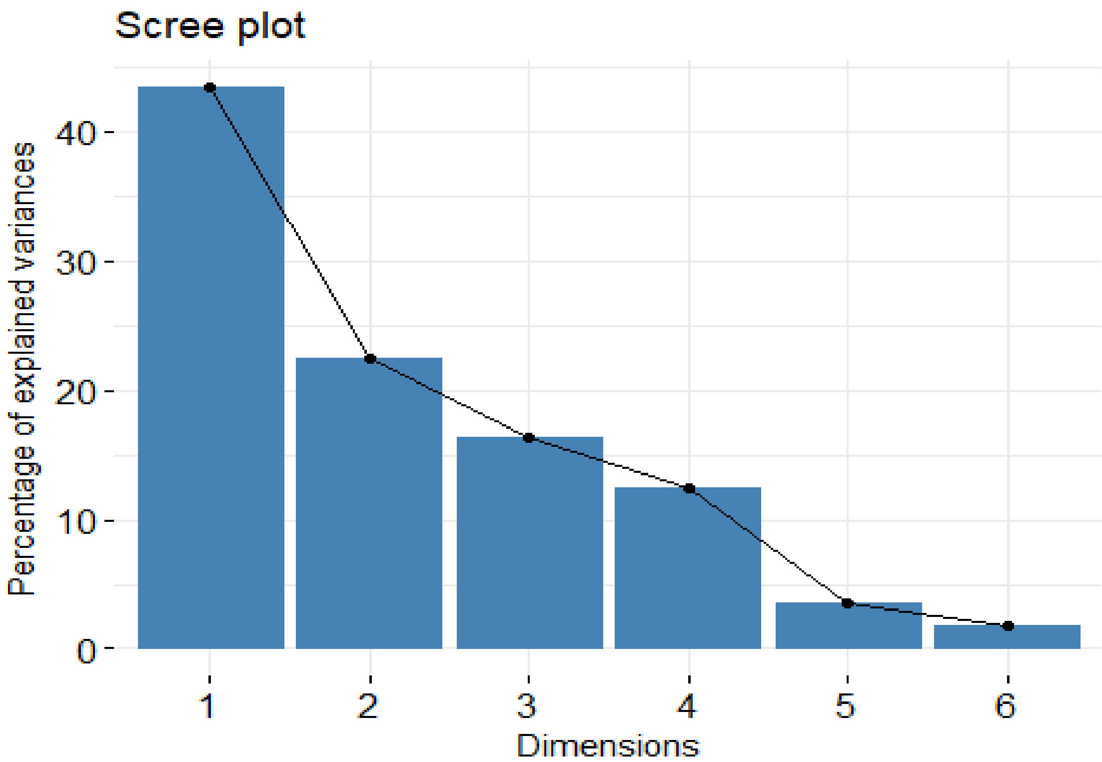


*Figure 3-6 Scree plot for each principal component/dimension.*

*Table 3-10 Eigenvalue and percentage of variance for each principal component.*

| Principal component | Eigenvalue | Percentage of variance |
|---|---|---|
| **1** | 2.601 | 43.355 |
| **2** | 1.343 | 22.388 |
| **3** | 0.984 | 16.410 |
| **4** | 0.749 | 12.487 |
| **5** | 0.214 | 3.559 |
| **6** | 0.108 | 1.802 |

The contribution of variables clay and sand were explained > 65% of the variation in Dim1, while phosphorus and nitrogen were explained > 60% in Dim2 (Table 4-11). Therefore, clay, sand, phosphorus, and nitrogen are the candidate of soil variables included in the model.

*Table 3-11 The contribution for each soil variable in each dimension.*

| Variable | Dimension 1 | Dimension 2 | Dimension 3 | Dimension 4 | Dimension 5 |
|---|---|---|---|---|---|
| **Clay** | 34.414 | 0.284 | 0.319 | 8.227e-01 | 21.038 |
| **Sand** | 29.857 | 2.745 | 1.057 | 8.637e+00 | 58.607 |
| **Phosphorus** | 2.531 | 41.220 | 4.215 | 4.274e+01 | 8.238 |
| **Nitrogen** | 0.636 | 32.862 | 20.384 | 4.546e+01 | 0.001 |
| **pH** | 11.644 | 14.878 | 43.688 | 4.334e+00 | 6.747 |
| **CEC** | 20.918 | 8.000 | 30.336 | 3.185e-04 | 5.370 |

A Linear model was performed to test the collinearity among the candidate of the variables (Table 4-12). We found that clay and sand were strongly correlated [$F_{(1,13)}$ = 14.92, Adj. $R^2$ = 0.5, *p-value* = 0.002] therefore sand will be dropped and will not be included in the model.

*Table 3-12 Linear model between each candidate of soil variables.*

| Variable tested | F statistic$_{(1,13)}$ | Adjusted $R^2$ | $P$ |
|---|---|---|---|
| **Clay ~ sand** | 14.92 | 0.499 | **0.002** |
| **Clay ~ phosphorus** | 1.38 | 0.027 | 0.261 |
| **Clay ~ nitrogen** | 0.119 | -0.067 | 0.736 |
| **Sand ~ phosphorus** | 0.004 | -0.077 | 0.949 |
| **Sand ~ nitrogen** | 0.320 | -0.051 | 0.581 |
| **Phosphorus ~ nitrogen** | 0.672 | -0.024 | 0.427 |

# 4

# Depletion of soil organic carbon stocks in Bornean logged forests

*Soil pit was dug to analyze both chemical and physical properties of soil in Malinau Research Forests (North Kalimantan)*

*(Picture by Andes Hamuraby Rozak)*

# Abstract

*Background and aims* The removal of largest trees in tropical forests through selective logging leads to a significant loss of above-ground biomass and reduction of litter production, which in turn might affect input of organic material in soil. This study quantifies this phenomenon and the reduction in soil organic carbon (SOC) stocks in a logged tropical Dipterocarp forest in Borneo.

*Methods* Fifteen (15) plots were established in a 16-years old logging concession, representing a logging gradient ranging from no to 55% reduction of initial biomass. Linear mixed models were developed to analyze the effect of logging intensity accounting for major determinant of SOC in soil, such as amount of litter above-ground, slope, available phosphorus and clay content up to 100 cm.

*Results* SOC stocks (0-100 cm) ranged from 40 to 52 Mg $ha^{-1}$. Two third of the stock measured was found in the 30 cm upper layer and 31% of the variance could be explained by logging intensity, slope, and clay content. Similarly, overall the variation of SOC stock (0-100 cm) was best explained by logging intensity, clay content, slope, and litter C stocks.

*Conclusions* SOC stocks were found to decrease linearly with logging intensity, decreasing by 30% in areas affected by high logging intensity. Owing the extent of logged or degraded forests on Borneo and more generally in South East Asia, a small but long-term decline in SOC stocks contributes to turn tropical forests into net source of carbon.



**Keywords**

Soil organic carbon, logging intensity, selective logging, tropical forests, Dipterocarp forests

## 4.1 Introduction

Soil organic carbon (SOC) contributes significantly to global carbon storage (Lal 2005; Smith 2012). In tropical forest ecosystems, SOC is the second largest carbon (C) pool, just after vegetation, and form around 44% of ecosystem C stocks (Lal 2005). SOC plays a pivotal role in the global C balance and up to 20% (approx. 78 Pg) of anthropogenic C emitted to the atmosphere since the industrial revolution could be related to soil degradation (Lal 2004). However, the magnitude and persistence of SOC depletion due to anthropogenic activities, such as agriculture or logging, remains poorly assessed, notably in complex ecosystems such as tropical forests.

At Borneo, logged and degraded forests are now outstripping intact forests (Gaveau et al. 2014), covering about 18 million ha. A small reduction in SOC stocks in logged forests could, therefore, have a significant effect on C budget at large scale. The depletion of SOC stocks due to logging has long been disregarded, whereas it can be a significant source of C emission (Lal 2004; Smith 2012; Pearson et al. 2017). A simulation of the evolution of SOC in a Dipterocarp forest estimated increased stocks short after logging (i.e during the first 10 years) and a sharp decrease after 50 years (Pinard and Cropper 2000). Similar results were observed in African forests where SOC was found to have decrease by 25% in logged forests (Chiti et al. 2015).

Selective logging of a few large commercial tree species, as traditionally practiced in Borneo, was shown to impact forest structure and composition (Sist et al. 1998; Sist, Sheil, et al. 2003; Sist and Nguyen-Thé 2002). By creating large canopy gaps (Asner et al. 2004; Inada et al. 2013), the production of litter is reduced (Prasetyo et al. 2015) and solar radiations and temperature on the forest floor sharply increase (Hardwick et al. 2015; Gaudio et al. 2017). Increased temperature of the forest floor were shown to stimulate litter decomposition (Salinas et al. 2011) and favor the decomposition of soil organic matter (Covington 1981; Raich et al. 2006). These different phenomena are likely causes explaining a reduction of SOC in logged tropical forests.

SOC stocks are naturally varying in space and time due to logging practices and environmental heterogeneity (Rozak et al. 2018). SOC were notably shown to vary with topography (Wei et al. 2008; Fissore et al. 2017), soil texture (Zinn, Lal, and Resck 2005), and phosphorus content (Dieter, Elsenbeer, and Turner 2010; Hou et al. 2014). For instance, topography determines water flows and thereby influences the transport of organic material in soil (Tsui, Chen, and Hsieh 2004). Soil texture is also important in determining C content. Clay content was found positively correlated with SOC (Jobbágy and Jackson 2000; Zinn, Lal, and Resck 2005), while phosphorus is generally a good indicator of soil fertility, influencing the amount of aboveground biomass (AGB) and tree species diversity (Paoli and Curran 2007; van der Sande et al. 2018). Those are in turn affecting SOC through root-related processes (Six et al. 2004). Such strong interdependency between plants and soil was notably found in Borneo, where variability in AGB and tree diversity was mainly explained by climatic and environmental variables, such as soil texture, soil fertility, elevation, and rainfall (Slik et al. 2009; Slik et al.

2010; Paoli, Curran, and Slik 2008). We, therefore, hypothesized that topography, soil texture, and available phosphorus will also affect SOC stocks at our study site.

Recently, the effect of logging on forest C stocks has received greater attention (e.g. Saner et al. 2012; Pfeifer et al. 2015; Rozak et al. 2018). However, studies specifically addressing the effect of logging on SOC stock remain scarce. Most of the few specific studies accounting for SOC stock used a mere distinction between logged and unlogged forests (e.g. Saner et al. 2012; Berenguer et al. 2014; Chiti et al. 2015) and failed to quantify logging intensity (but see van der Sande et al. 2018; Rozak et al. 2018). Logging intensity was greatly vary among tropical regions and South East Asian forests are among the most productive (Blaser et al. 2011; FAO 2016). Incidental damages (Sist et al. 1998; Sist, Sheil, et al. 2003; Sist and Nguyen-Thé 2002) and coarse wood debris (Rozak et al. 2018) were shown to correlate linearly with logging intensity in Dipterocarp forests. We, therefore, hypothesized that SOC stocks are also responding to logging intensity and explored this relationship in a 16-year old logged forest in Borneo. Specifically, our study quantified SOC stocks (up to 100 cm depth) and tested for any effect of logging intensity on SOC stocks in controlling for other environmental drivers, namely the amount of litter above-ground, available phosphorus, clay content, and slope.

## 4.2 Materials and methods

### 4.2.1 Study site

The study was conducted in Malinau Research Forest (MRF), North Kalimantan (2°45’N, 116°30’E). This experimental network consists of 24 1-ha permanent sample plots, established in 1998/1999 to support sustainable forest management practice in mixed Dipterocarp forests (Sist, Sheil, et al. 2003). The plots were randomly established based on the density of harvestable timber trees (DBH >60 cm) before logging. MRF was selectively logged in 1999/2000 with different logging intensity, ranging from 3 to 13 trees felled ha$^{-1}$ and the targeted commercial tree species were *Agathis borneensis*, *Dipterocarpus* spp., and *Shorea* spp. (Sist, Sheil, et al. 2003). While Dipterocarps are dominating, MRF is among the most diverse Indonesian forests with 205 tree species and 759 stems of tree inventoried per hectare (Sheil et al. 2010). The forest is 100 to 300 m above sea level with 10-70% slope and an annual rainfall of 3,790 mm (Sist, Sheil, et al. 2003). The soil in MRF was classified as Ultisols (more detail information can be found in CIFOR and ITTO 2002). Due to high rainfall, the soils are constantly wet and ultisols were characterized by a high degree of weathering with a pH of around 4.5 and low fertility with only 20% base saturation (CIFOR and ITTO 2002).

## 4.2.2 Logging intensity, soil sampling and litter

Seven of the permanent plots were surveyed in 2016 (detailed description can be found in Rozak et al. 2018). Each plot was divided into 4 subplots (50 m *x* 50 m) to account for logging heterogeneity in the plot (Rozak et al. 2018). Logging intensity is defined as the percentage of initial biomass lost (i.e. harvested and killed/smashed trees), calculated in each subplot as the relative difference between biomass stocks estimated at pre-logging (1998) and first post-logging (2000). Above-ground biomass (AGB) of live trees (DBH >20 cm) was estimated using a generic allometric model (Chave et al. 2014), that has been shown to perform well in logged Dipterocarp forests (Rutishauser et al. 2013).

Two soil pits were randomly dug in each plot (except in subplot C09 where 3 pits were dug) leading to 15 soil pits in total. All soil pits were placed between the top and toe of the slope and measured with a clinometer (Suunto Pm-5). Soil samples were collected at five fixed layers (0-5, 5-15, 15-30, 30-50, and 50-100 cm) to determine both chemical and physical properties. Chemical analyses included C concentration (Walkley and Black 1934), pH ($H_2O$), available phosphorus (Bray II, Bray and Kurtz 1945), and physical properties such as bulk density, a fraction of gravel (>2 mm), and soil texture. In order to determine soil bulk density and the gravel fraction, a soil sample of each layer was collected using a metal ring with an inner diameter of 48.5 mm and a height of 50 mm (approx. 92 $cm^3$).

The litter layer (or organic horizon) was collected using a 1 x 1 m frame on top each soil pit. The litter layer is defined as all dead organic material and deadwood with a diameter <10 cm lying on the soil surface. The litter was weighed wet using a hanging scale. A sub-sample (<0.5 kg) was then oven-dried (80° C) until constant weight to estimate the dry weight. Dry mass of litter was calculated based on the wet-to-dry weight ratio of sub-samples. The litter layer C stock was then estimated by multiplying litter mass by 47% as a default C concentration by IPCC (2006).

## 4.2.3 Calculations of soil mass and SOC stocks

Soil mass (*SM,* Mg $ha^{-1}$) and SOC stocks (*SOC*, Mg $ha^{-1}$) of each sampled layer ($d_i$, 0-5, 5-15, 15-30, 30-50 and 50-100) were calculated without the coarse fragment (*CF*, <2 mm):

$$SM_i = d_i \cdot \rho_i \cdot (100 - CF_i) \cdot 10^4$$
$$SOC_i = SM_i \cdot OC_i$$

where $\rho_i$ is the bulk density (g $cm^{-3}$) and *OC* is the organic C concentration of the specific layer, (mg C $g^{-1}$). Soil mass and SOC stocks were also calculated for accumulated layers 0-5, 0-15, 0-30, 0-50 and 0-100 cm.

### 4.2.4 Statistical analysis

Linear mixed models were developed to test for the effect of logging intensity, topography (slope), clay content, available phosphorus, and amount of litter C stock above each soil pit, on SOC stock at each layer (0-5, 5-15, 15-30, 30-50, and 50-100 cm) and accumulated across layers (0-5, 0-15, 0-30, 0-50, and 0-100 cm). The amount of SOC stock (*Y*) at each layer or accumulated across layers was modeled as follows:

$$Y = \beta_0 + \beta_1 \cdot logging\ intensity + \beta_2 \cdot slope + \beta_3 \cdot clay + \beta_4 \cdot available\ phosphorous + \beta_5 \cdot litter\ C\ stock + u + \varepsilon_a$$

Where $\varepsilon_a$ is an error term and β are the coefficient of each predictor tested in the model. Pairwise scatterplots and linear models were performed to evaluate collinearity among explanatory variables. Collinearity among covariates was avoided in the model to avoid variance inflation of regression's parameters that could potentially lead to erroneous identification of relevant variables (Dormann et al. 2013). Initial forest structure was assumed to be non-independent within the plot, and therefore plots were accounted for as a random factor (*u*) to lower spatial autocorrelation. For each layer, logging intensity and available phosphorus were log-transformed to fulfill normality and avoid heteroscedasticity of the residuals. Q-Q plots were visually evaluated to validate the different models. Analysis of variance (ANOVA) was performed to test for differences in SOC stocks, C concentrations, available phosphorus, and clay content among soil layers. Further, the selection of the most parsimonious model was carried out through model-averaging for each layer and each accumulated layer. The importance value of each variable in the model retained was computed as the sum of the weights or probabilities to be retained across all models tested.

All analyses were performed in R language (R Core Team 2017) using the following packages: "lme4" (Bates et al. 2015) to fit linear mixed models, "glmulti" (Calcagno and de Mazancourt 2010) to predict the best fit model based on the lowest Bayesian Information Criterion (BIC) as well as to estimate the relative importance value of each explanatory variable, "MuMIn" (Barton 2016) to extract marginal (the proportion of variance explained by the explanatory variables) and conditional (the proportion of variance explained by the explanatory variables and random (i.e. plot) factors) $R^2$ of the best model, and "car" (Fox and Weisberg 2011) to analyze significance in differences between explanatory variables.

## 4.3 Results

### 4.3.1 Overview of logging intensity, litter C stocks, C concentration, available phosphorus, and clay content

At our site, logging intensity ranged from 0 to 55% (mean 12.4%) of initial biomass lost (Table 4-4). Slopes ranged between 12 and 66% (mean 36.6%). Litter C stocks averaged 4.1 Mg C ha$^{-1}$ (range 3-5.5 Mg C ha$^{-1}$), while C concentration in soil averaged 22 g kg$^{-1}$ (range 12-30 g kg$^{-1}$) in the first 5 cm layer and decreased significantly to 4 g kg$^{-1}$ (range 1-3 g kg$^{-1}$) in the deepest layer (50-100 cm) (Figure 4-1A). Average phosphorus content was 8.2 µg g$^{-1}$ (range 4.3-17.9 µg g$^{-1}$) in the first layer (0-5 cm) and decreased significantly to 4 µg g$^{-1}$ (range 3-6.5 µg g$^{-1}$) in the deepest layer (50-100 cm) (Figure 4-1B). The average of clay contents was 20% (range 10-30%) in the upper layer (0-5 cm) and increased significantly to 33.5% (range 22.8-45%) in the deepest layer (50-100 cm) (Figure 4-1C).

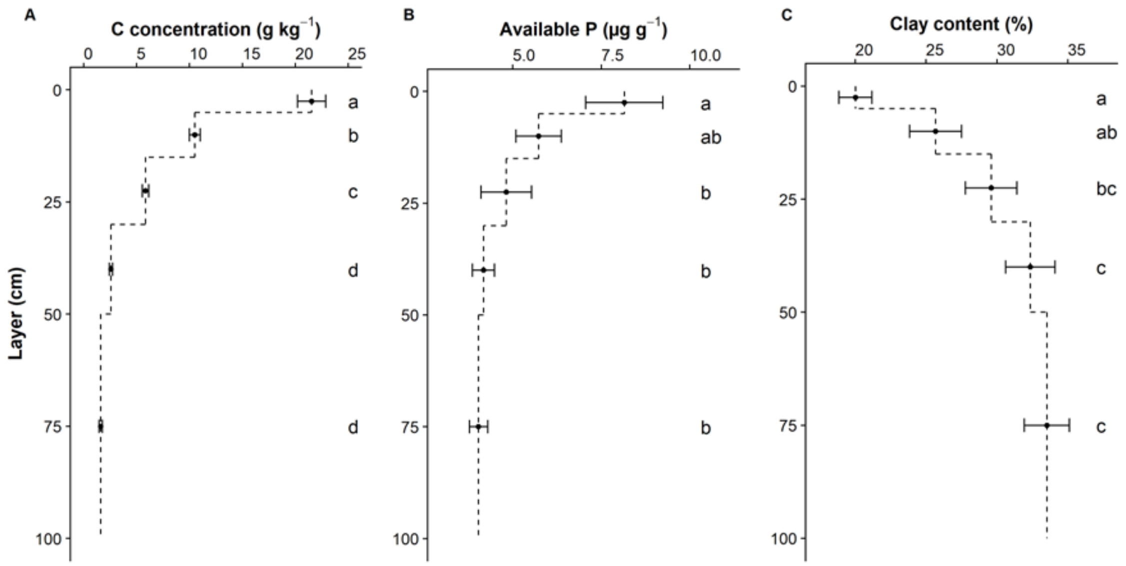


*Figure 4-1 Variability of (A) concentrations of soil organic C (mg g$^{-1}$), (B) available phosphorus (µg g$^{-1}$), and (C) clay content (%) by each soil layer. Bars show standard error of the mean and letters indicate significant differences among layer after Tukey's post-hoc contrasts (P <0.05).*

## 4.3.2 Soil mass and SOC stocks

Soil mass (0-100 cm layer) in MRF averaged 14 Gg $ha^{-1}$ (Figure 4-2A) and stored in average 46 Mg $ha^{-1}$ of SOC stocks (Figure 4-2B). About two third of SOC (30 Mg $ha^{-1}$) were found in the upper 30 cm layer even though average soil mass at this accumulation layer represented a third of total soil mass sampled (0-100 cm). SOC stock in layer 30-50 cm to be significantly lower than that SOC stock in the other layers (Tukey contrasts, $P$ <0.01).

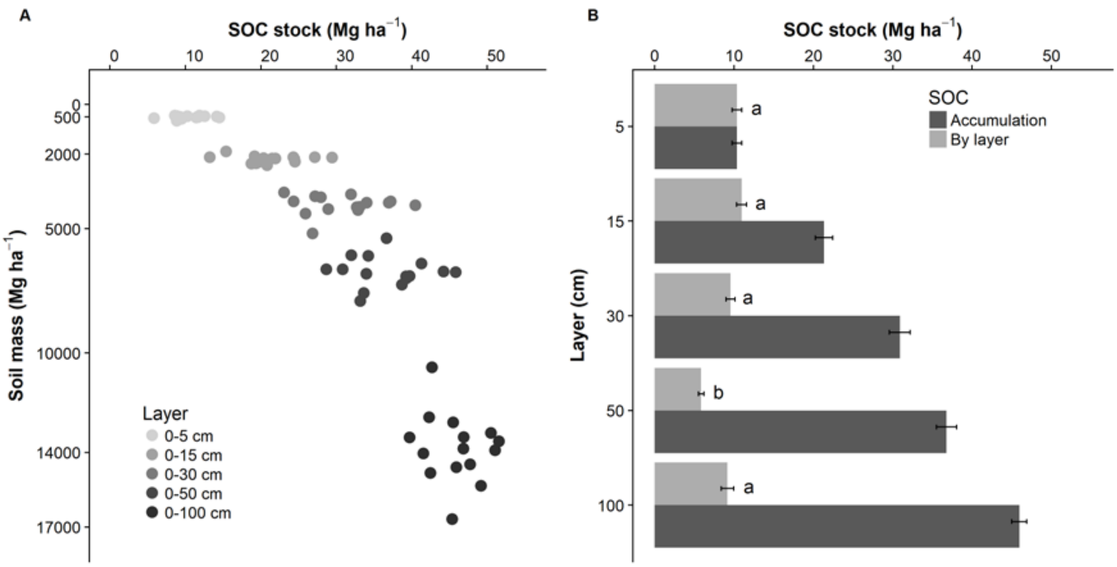


*Figure 4-2 Variation of SOC stocks along soil mass across 15 0.25-ha subplots (A) and SOC stocks (B) by layer (light gray solid bar) and accumulated SOC stock (dark grey solid bar). Bars show standard error of the means. Letters show significant differences among layers.*

Cumulated SOC up to 100 cm tend to decrease with increasing logging intensity, even though the correlation was not significant (Figure 4-3, Adj. $R^2$ = 5%, *P* >0.1). Excluding a plot where no logging occurred (0% logging intensity) slightly improved this relationship and logging intensity marginally influenced SOC stocks (Figure 4-3, blue line, Adj. $R^2$ = 22%, *P* = 0.06).

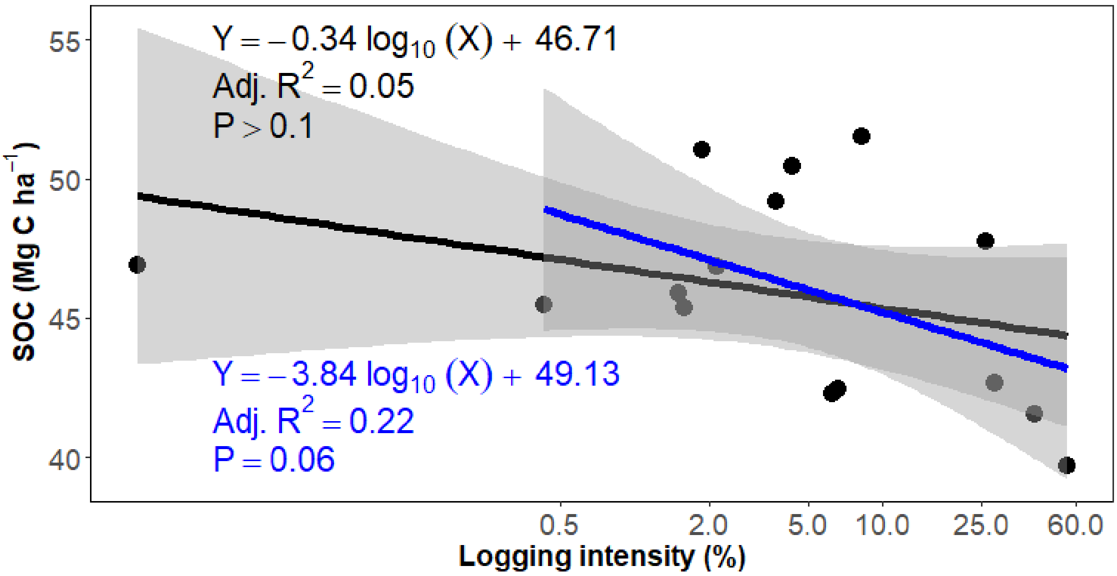


*Figure 4-3 SOC stocks along a gradient of logging intensity. The solid black line shows a linear model with 95% confidence interval (n = 15). The solid blue line shows a linear model excluding plot where no logging ioccured with 95% confidence interval (n = 14).*

### 4.3.3 Drivers of SOC stocks

The effect of predictors tested was evident only in the first 3 upper layers (Table 4-1). In general, the slope was a good predictor of SOC stocks in these three layers but had contrasting effects. SOC stock in the top layer (0-5 cm) was negatively influenced by slope (β = -3.1, P = 0.04), while it was positively correlated with slope at the deeper layer (15-30 cm, β = 4, P = 0.05). Logging intensity was found to be marginally significant (P = 0.06) only at a layer 5-15 cm. The best fit models for layer 0-5 and 5-15 cm explained only 16% and 26%, respectively, of the variation in SOC stocks. At layer 15-30 cm, SOC stocks were best explained by the slope, explaining 16% of the total variance.

*Table 4-1 The goodness of fit (BIC, marginal and conditional $R^2$), coefficients (β), standard errors (SE), and p-values (P, significant values are in bold) of the best model retained for each layer in MRF.*

| Layer (cm) | BIC | Marginal $R^2$ | Conditional $R^2$ | Predictor | β | SE | *P* |
|---|---|---|---|---|---|---|---|
| **0-5** | 68.1 | 16% | 85% | **Intercept** | **12.8** | **2.5** | **<0.001** |
| | | | | **Slope** | **-3.1** | **1.2** | **0.04** |
| | | | | Available phosphorus | 2.7 | 1.4 | 0.09 |
| **5-15** | 75.9 | 26% | 49% | Intercept | 3.8 | 3.6 | 0.32 |
| | | | | Logging intensity | -0.8 | 0.4 | 0.06 |
| | | | | Slope | 5.5 | 2.5 | 0.06 |
| **15-30** | 70.7 | 16% | 63% | Intercept | 3.5 | 2.8 | 0.25 |
| | | | | **Slope** | **4.0** | **1.8** | **0.05** |
| **30-50*** | 55.2 | 0 | 54% | Intercept | 5.9 | 0.4 | 14.1 (t-value) |
| **50-100*** | 79.9 | 0 | 57% | Intercept | 9.3 | 1.0 | 9.46 (t-value) |

* SOC stocks were only influenced by a random factor.

Considering SOC stocks accumulated across layers, logging intensity was found to significantly negatively affect SOC stocks at three layers: 0-15, 0-30, and 0-100 cm (Table 4-2). The best models for that three layer were always a combination of logging intensity and other variables. In contrast with the effect of slope, increasing logging intensity consistently reduced SOC stocks. SOC stocks (0-100 cm) were best explained by logging intensity, clay content, litter C stock, and slope (all *P* <0.05). Overall, the different models explained only 16-58% of the total variance in accumulated SOC stocks.

*Table 4-2 The goodness of fit (BIC, marginal and conditional $R^2$), the coefficient (β), standard error (SE), and p-value (P, significant values are in bold) of the best model retained for each accumulation SOC stocks in MRF.*

| **Layer (cm)** | **BIC** | **Marginal $R^2$** | **Conditional $R^2$** | **Predictor** | **β** | **SE** | ***P*** |
|---|---|---|---|---|---|---|---|
| **0-5** | 68.1 | 16% | 85% | **Intercept** | **12.8** | **2.5** | **<0.001** |
| | | | | **Slope** | **-3.1** | **1.2** | **0.04** |
| | | | | Available phosphorus | 2.7 | 1.4 | 0.09 |
| **0-15** | 86.3 | 58% | 81% | Intercept | -3.4 | 7.9 | 0.68 |
| | | | | **Logging intensity** | **-1.1** | **0.4** | **0.03** |
| | | | | **Clay** | **0.6** | **0.2** | **0.01** |
| | | | | **Phosphorus** | **16.3** | **5.5** | **0.01** |
| **0-30** | 94.1 | 31% | 79% | Intercept | 12.5 | 7.2 | 0.11 |
| | | | | **Logging intensity** | **-1.4** | **0.7** | **0.05** |
| | | | | Clay | 0.3 | 0.2 | 0.06 |
| | | | | **Slope** | **7.8** | **3.4** | **0.05** |
| **0-50*** | 94.1 | 0 | 61% | Intercept | 36.9 | 1.6 | 22.6 (t-value) |
| **0-100** | 80.9 | 29% | 93% | Intercept | 53.9 | 5.1 | **<0.001** |
| | | | | **Logging intensity** | **-1.1** | **0.4** | **0.02** |
| | | | | **Clay** | **-0.3** | **0.1** | **0.02** |
| | | | | **Litter** | **-1.8** | **0.6** | **0.02** |
| | | | | **Slope** | **6.8** | **1.9** | **0.01** |

* SOC stocks were only influenced by a random factor.

Considering the full model, logging intensity reduced cumulated SOC stocks (0-100 cm, Figure 4-4B) sixteen years after logging (detailed value presented in supplementary Table 4-5 and Table 4-6). Variability of cumulated SOC stocks (layer 0-100) was also strongly influenced by clay and slope that had a relative importance of 62% and 71%, respectively. While for layer 0-30 cm (the minimum reporting layer required by IPCC), the variability was influenced by slope and logging intensity with relatively low importance values of 45 and 35%, respectively.

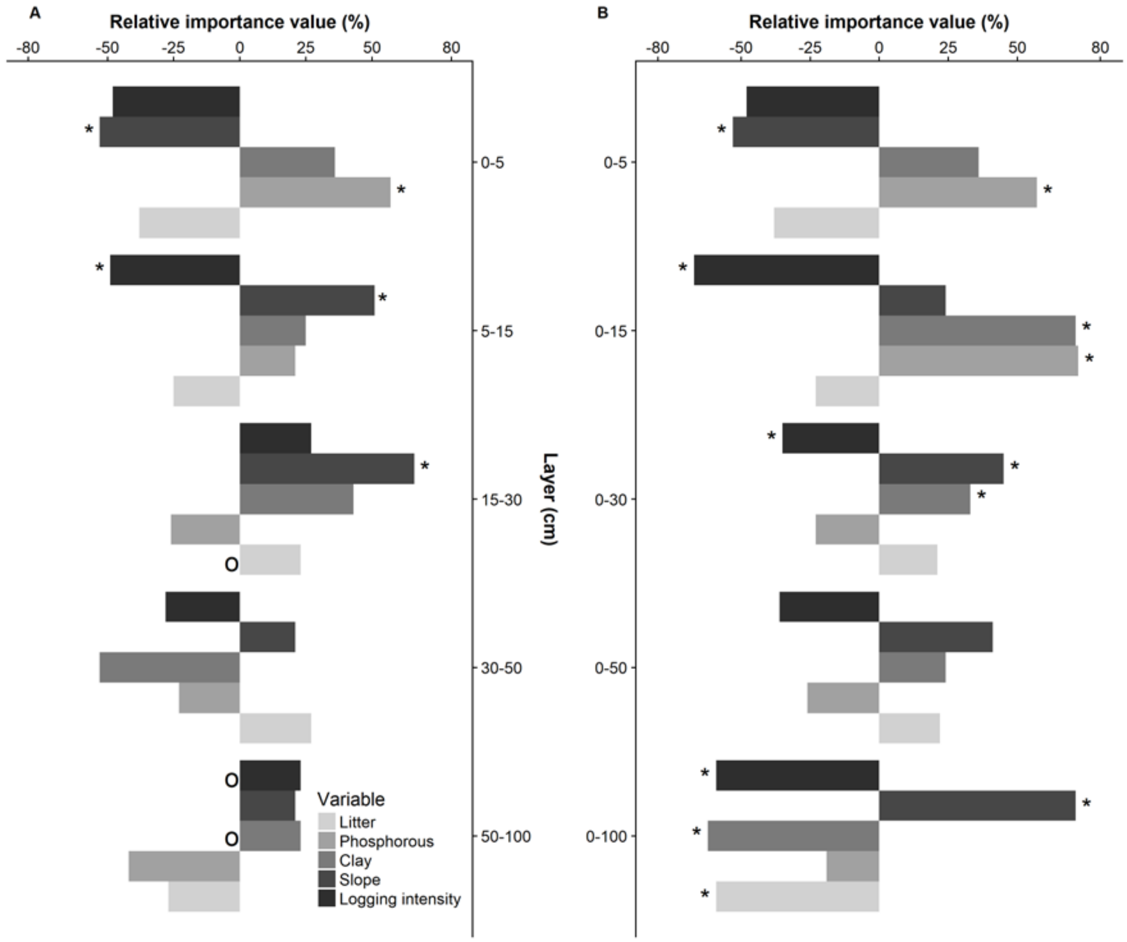


*Figure 4-4 The relative importance (%) of logging intensity, slope, clay, available phosphorus, and litter C stocks in determining SOC stocks by layer (A) or accumulated across layers (B). Negative or positive importance values indicate the influence of each variable on SOC stocks. Letter "o" indicates when a variable is spanning 0. Asterisks show variables retained in the most parsimonious models at each layer.*

## 4.4 Discussion

The effect of selective logging on SOC stocks in the tropical region has only recently been addressed (e.g. Olander et al. 2005; Saner et al. 2012; Berenguer et al. 2014; Chiti et al. 2015; van der Sande et al. 2018) with contrasting results. For instance, Chiti et al. (2015) reported a 40% decrease in SOC (layer 0-5 cm) 10 years after logging in African tropical forests logged at low intensity (1-2 trees $ha^{-1}$). On the other hand, no effect was found 6 years after logging in Guyana forests logged intensively (up to 8 trees $ha^{-1}$) (van der Sande et al. 2018). However, the difference of these studies seems particularly due to several variables such as the differences in environmental variables (climate, rainfall, soil type, slope), biomass production, and logging intensity. Our study estimated SOC stocks in Bornean Dipterocarp forests 16 years after logging and tested several potential drivers. We found that logging explained SOC stocks at four layers: 5-15, 0-15, 0-30, and 0-100 cm, in conjunction with other factors. Overall, SOC stocks were negatively affected by logging intensity (Table 4-2,Figure 4-4), decreasing up to 12% in areas intensively logged. Accounting for several proximal drivers, logging intensity had a significantly negative effect on SOC in about 60% of all combinations tested (Figure 4-4B). Logging intensity is expected to influence forest structure and forest damage and therefore expected to influence SOC stocks. Logging results in high amount of unintended damages and wastes, and strongly modify the conditions near the soil surface. The mortality of damaged trees may last for more than a decade (Blanc et al. 2009; Lussetti et al. 2016) and depends on logging intensity (Sist and Nguyen-Thé 2002; Sist, Sheil, et al. 2003), forming a continuous input of organic material to upper soil layers.

While SOC stocks in the top 5 cm were mainly influenced by slope and available phosphorus (Table 4-2), the effect of logging was more pronounced in accumulated layer below 5 cm. This result is in line with those found in Guyana where no effect of logging was detected on SOC stocks (van der Sande et al. 2018). In the top layer, the effect of slope outpaced all other variables, suggesting some sort of homogenization on this layer due to the water runoff and litter transport. Organic materials in the soil surface were able to translocate faster by water in a higher slope, and therefore to significantly decrease SOC stocks when, for example, rain happens (Gregorich and Anderson 1985; Tsui, Chen, and Hsieh 2004). The slope influence is related to the rainfall intensity and rainfall was found as the main driver of C concentration at the soil surface (Hobley and Wilson 2016). While organic materials in the surface (0-5 cm) translocate faster in the higher slope, organic materials in the deeper layers (>5 cm) might move downward (Bruun et al. 2007; Dörr and Münnich 1989). Our result, therefore, suggests that the top layer may act as a buffer. Further, available phosphorus might also indirectly affect SOC stocks through the enhanced of above-ground biomass and productivity (Paoli and Curran 2007). Available phosphorus is used as soil fertility indicator and therefore positively affect above-ground biomass (van der Sande et al. 2018) which in turn influencing SOC stocks. We found a positive influence of available phosphorus on SOC stocks for layer 0-5 and 0-15 cm (Figure 4-4) that corroborates the study in tropical lowland forests of Panama (Dieter, Elsenbeer, and Turner 2010).

Going deeper in soil, things are getting clearer and might reveal where the microbial activity occurs and how it reacts to changing conditions. For the deeper accumulated layer, we found all variables except available phosphorus explained SOC stocks (Table 4-2). The effect of logging intensity was perceptible across all layers below 5 cm. SOC stocks (0-100cm) decreased with increasing logging intensity (Figure 4-3), being in average 15% lower in logged areas compared to unlogged areas. Similar results were found in African logged forests, where SOC decreased by 20% in 18-year old logged forests (Chiti et al. 2015) and through a long-term simulation in a Dipterocarp forest (Pinard and Cropper 2000). In this last study, a sharp decrease (approx. 50%) of SOC stocks (0-50 cm) was predicted from 10 to 50 years after intensive conventional logging.

### 4.4.1 Wet combustion method underestimating SOC stocks in a logged forest

Sixteen years after logging, SOC stock averaged 46 Mg ha$^{-1}$ (layer 0-100 cm), in range with the value reported for Dipterocarp forests (Ohta and Effendi 1992; Saner et al. 2012). However, measured SOC stocks (0-100 cm) were relatively low compared to values reported for a secondary Dipterocarp forests in Singapore (Ngo et al. 2013) and African logged forests (Chiti et al. 2015), where SOC averaged 78-104 and 90-150 Mg ha$^{-1}$, respectively. In the top 30 cm, where 30% of the total soil masses (0-100 cm) is found, SOC stocks averaged 31 Mg ha$^{-1}$ similar to what was found in a 16 years old logged Dipterocarp forest in the Philippines (30-40 Mg ha-1, Lasco et al. 2006). Higher values were reported in degraded Amazonian forests which reached 43-63 Mg ha$^{-1}$ (Berenguer et al. 2014). Our study and two other studies (Saner et al. 2012; Lasco et al. 2006) are based on the wet digestion method (Walkley and Black 1934), while the three other studies (Ngo et al. 2013; Chiti et al. 2015; Berenguer et al. 2014) were using the dry combustion method. The wet digestion method utilizes oxidation by $H_2SO_4$ and dichromate at 120° C. This temperature may be sufficient to oxidize labile organic C but insufficient for elemental C forms such as stable and recalcitrant forms (Allison 1960). Hence, the major limitation of this method is that the oxidation of the organic C is incomplete and therefore underestimate C concentration compared to the dry combustion method (De Vos et al. 2007; Lettens et al. 2007). Although wet combustion method has some limitations, it seems applicable for a rapid estimation of the soil C concentration (Saner et al. 2012; Lasco et al. 2006). Correction factors of 1.3 to 2.4 have been proposed (De Vos et al. 2007; Krishan et al. 2009; Lettens et al. 2007) in order to adjust C concentration from wet to dry combustion method result. However, due to large variability in soil C among soil types and depths, Allison (1960) suggested to calculate a specific correction factor for any soil type. Therefore, the correction factor is only valid for the specific soil type tested only and will lack of accuracy if employed for other soil types (Lettens et al. 2007). Taking this correction factor into account, regardless soil types and depth, SOC stocks in our study site were comparable to those in SE Asia, African, and Amazonian logged forests and in the spectrum with the reference of SOC stocks value provided in IPCC guidelines (2006) for 0-30 cm layer (47 Mg ha$^{-1}$ for tropical moist forests).

### 4.4.2 Effect of litter C stocks on SOC stocks

Our results found that total measured SOC stocks (0-100 cm) were negatively affected by litter C stock (Figure 5-4B). While appearing counter-intuitive at a first glance, this result may be explained by the recruitment and abundance of pioneer species short after logging. Indeed abundance and growth of pioneers was shown to be positively correlated with logging intensity (Lussetti et al. 2016), peaking 10-20 years after logging (Pinard and Cropper 2000). This group was shown to have higher leaf phosphorus and nitrogen content than climax species (Raaimakers et al. 1995), increasing palatability of decomposer (Deyn, Cornelissen, and Bardgett 2008) and potentially stimulating the microbial activity. Ultimately, enhanced microbial activity could lead to the consumption of organic matter stored in deeper layers, a phenomenon described as “priming effect” (Fontaine et al. 2004).

### 4.4.3 Integrating SOC for greenhouse gas emissions calculation

Accurate estimation of C emissions from deforestation and degradation continue to be challenging and requiring extensive financial incentives (Khun and Sasaki 2014b). The importance of SOC stocks in Land Use, Land-Use Change, and Forestry (LULUCF) initiatives has remained overlooked (Graham et al. 2017; but see Griscom, Ellis, and Putz 2014). Our results stress the importance of accounting for SOC stocks when estimating the C budget of logging in tropical forests. Assuming constant soil properties, the removal of half of the initial biomass at a site could reduce SOC stocks by approx. 15%. Therefore, our results point toward a better integration of soil C in “C-oriented forest management” and when estimating greenhouse gas emissions from logging.

## 4.5 Conclusion

Our main finding showed that SOC stocks in the 30 cm upper layer and the total stocks (0-100 cm layer) were explained and negatively affected by logging intensity. Even though logging intensity was not the sole variable explaining the variabilities of SOC stocks, we recommend that SOC measurements should be included as a potential contributor to C emissions due to logging. Indeed, Pearson et al. (2017) has included C emissions from soils for their emission estimation. However, their C emission estimation, particularly for non-peat soils, is based on HWSD database (FAO/IIASA/ISRIC/ISS-CAS/JRC 2009) and land use change soil factors (IPCC 2006). Therefore, more research on SOC in logged forests is needed due to the different level of logging intensities among forest concessionaires and our results provide a first step towards the precise estimate of C emissions due to logging.

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## Supplementary tables

*Table 4-3 Pre-logging forest structure, biomass loss, and logging intensity (%) at 0.25-ha subplot scale. Pre-logging forest structure includes number of pre-logging stem (tree), pre-logging basal area ($m^2$), and pre-logging biomass (Mg). Biomass loss includes number of tree harvested (tree), tree biomass harvested (Mg), number of tree killed (tree), and tree biomass killed (Mg) due to logging.*

| Plot | Subplot | Number of stems | Basal area | Pre-logging biomass | Number of trees harvested | Biomass harvested | Number of trees killed | Biomass killed | Logging intensity |
|---|---|---|---|---|---|---|---|---|---|
| **MRF-C12** | MRF-C12-3 | 62 | 8.23 | 104.75 | 0 | 0.00 | 1 | 3.86 | 3.69 |
| | MRF-C12-4 | 75 | 10.95 | 121.83 | 0 | 0.00 | 1 | 2.59 | 2.12 |
| **MRF-R12** | MRF-R12-1 | 57 | 6.27 | 68.56 | 0 | 0.00 | 1 | 0.29 | 0.42 |
| | MRF-R12-3 | 82 | 12.34 | 165.49 | 0 | 0.00 | 0 | 0.00 | 0 |
| **MRF-R01** | MRF-R01-1 | 54 | 7.18 | 83.25 | 0 | 0.00 | 1 | 1.55 | 1.87 |
| | MRF-R01-2 | 93 | 10.61 | 116.10 | 1 | 1.72 | 0 | 0.00 | 1.48 |
| **MRF-R02** | MRF-R02-1 | 65 | 6.73 | 72.99 | 2 | 9.53 | 1 | 0.51 | 8.14 |
| | MRF-R02-3 | 80 | 6.66 | 70.96 | 0 | 0.00 | 10 | 3.44 | 4.33 |
| **MRF-R06** | MRF-R06-2 | 46 | 4.28 | 47.15 | 1 | 3.74 | 9 | 8.42 | 25.80 |
| | MRF-R06-4 | 62 | 7.89 | 84.89 | 2 | 5.37 | 6 | 3.20 | 6.57 |
| **MRF-R07** | MRF-R07-1 | 60 | 7.80 | 99.59 | 4 | 32.24 | 12 | 9.16 | 40.87 |
| | MRF-R07-2 | 61 | 6.25 | 63.08 | 0 | 0.00 | 1 | 0.99 | 1.57 |
| **MRF-C09** | MRF-C09-1 | 75 | 13.64 | 182.31 | 5 | 36.34 | 19 | 18.57 | 28.15 |
| | MRF-C09-2 | 55 | 7.90 | 98.21 | 0 | 0.00 | 13 | 7.05 | 6.22 |
| | MRF-C09-3 | 83 | 11.30 | 117.99 | 5 | 36.08 | 31 | 30.95 | 54.83 |

*Table 4-4 Logging intensity, slope, litter C stock and by layer C concentration (Walkley-Black), available P (Bray) and clay content of the investigated 0.25-ha plots.*

| Variables | Layer (cm) | Units | Average | Minimum | Maximum |
|---|---|---|---|---|---|
| **Logging intensity** | - | % | 12.4 | 0 | 54.8 |
| **Slope** | - | % | 36.6 | 12.0 | 66.0 |
| **Litter** | - | Mg C $ha^{-1}$ | 4.1 | 3.0 | 5.5 |
| **C concentration** | 0-5 | mg $g^{-1}$ | 2.2 | 1.2 | 3.0 |
| | 5-15 | mg $g^{-1}$ | 1.1 | 0.7 | 1.4 |
| | 15-30 | mg $g^{-1}$ | 0.6 | 0.4 | 0.8 |
| | 30-50 | mg $g^{-1}$ | 0.3 | 0.2 | 0.4 |
| | 50-100 | mg $g^{-1}$ | 0.2 | 0.1 | 0.3 |
| **Available phosphorus** | 0-5 | µg $g^{-1}$ | 8.2 | 4.3 | 17.9 |
| | 5-15 | µg $g^{-1}$ | 5.7 | 3.2 | 13.1 |
| | 15-30 | µg $g^{-1}$ | 4.8 | 3.0 | 14.4 |
| | 30-50 | µg $g^{-1}$ | 4.2 | 2.7 | 6.4 |
| | 50-100 | µg $g^{-1}$ | 4.0 | 3.0 | 6.5 |
| **Clay** | 0-5 | % | 20.0 | 10.0 | 30.5 |
| | 5-15 | % | 25.7 | 10.2 | 40.6 |
| | 15-30 | % | 29.6 | 12.9 | 43.5 |
| | 30-50 | % | 32.4 | 14.8 | 40.6 |
| | 50-100 | % | 33.5 | 22.8 | 45.0 |

*Table 4-5 Model-averaged importance (%) of each fixed factor included in the model i.e. logging intensity, slope, litter, clay, and available phosphorus for each accumulated depth.*

| Depth (cm) | Fixed factor | Estimate | Variance | Relative importance value (%) |
|---|---|---|---|---|
| **0-5** | Phosphorus | 1.90 | 4.53 | 57 |
| | Slope | -1.66 | 3.50 | 53 |
| | Logging intensity | -0.26 | 0.11 | 48 |
| | Litter | -0.31 | 0.34 | 38 |
| | Clay | 0.02 | 0.01 | 36 |
| **0-15** | Phosphorus | 11.08 | 80.46 | 72 |
| | Clay | 0.37 | 0.09 | 71 |
| | Logging intensity | -0.76 | 0.46 | 67 |
| | Slope | 0.53 | 1.74 | 24 |
| | Litter | -0.03 | 0.07 | 23 |
| **0-30** | Slope | 2.56 | 12.12 | 45 |
| | Logging intensity | -0.31 | 0.28 | 35 |
| | Clay | 0.08 | 0.02 | 33 |
| | Phosphorus | -0.56 | 4.17 | 23 |
| | Litter | 0.04 | 0.09 | 21 |
| **0-50** | Slope | 2.51 | 13.89 | 41 |
| | Logging intensity | -0.36 | 0.35 | 36 |
| | Phosphorus | -1.76 | 16.39 | 26 |
| | Clay | 0.03 | 0.01 | 24 |
| | Litter | 0.04 | 0.12 | 22 |
| **0-100** | Slope | 4.31 | 12.27 | 71 |
| | Clay | -0.20 | 0.03 | 62 |
| | Litter | -0.92 | 0.97 | 59 |
| | Logging intensity | -0.63 | 0.44 | 59 |
| | Phosphorus | -0.98 | 6.58 | 19 |

*Table 4-6 Model-averaged importance (%) of each fixed factor included in the model i.e. logging intensity, slope, litter, clay, and available phosphorus for each depth.*

| Depth (cm) | Fixed factor | Estimate | Variance | Relative importance value (%) |
|---|---|---|---|---|
| **0-5** | Phosphorus | 1.90 | 4.53 | 57 |
| | Slope | -1.66 | 3.50 | 53 |
| | Logging intensity | -0.26 | 0.11 | 48 |
| | Litter | -0.31 | 0.34 | 38 |
| | Clay | 0.02 | 0.01 | 36 |
| **5-15** | Phosphorus | 0.09 | 0.74 | 21 |
| | Clay | 0.02 | 0.00 | 25 |
| | Logging intensity | -0.33 | 0.18 | 49 |
| | Slope | 2.52 | 9.61 | 51 |
| | Litter | -0.12 | 0.10 | 25 |
| **15-30** | Slope | 2.86 | 6.36 | 66 |
| | Logging intensity | 0.08 | 0.03 | 27 |
| | Clay | 0.05 | 0.00 | 43 |
| | Phosphorus | -0.62 | 1.90 | 26 |
| | Litter | 0.00 | 0.03 | 23 |
| **30-50** | Slope | 0.01 | 0.07 | 21 |
| | Logging intensity | -0.05 | 0.01 | 28 |
| | Phosphorus | -0.25 | 0.61 | 23 |
| | Clay | -0.05 | 0.00 | 53 |
| | Litter | 0.07 | 0.03 | 27 |
| **50-100** | Slope | 0.11 | 0.54 | 21 |
| | Clay | 0.00 | 0.00 | 23 |
| | Litter | -0.21 | 0.18 | 27 |
| | Logging intensity | 0.00 | 0.01 | 23 |
| | Phosphorus | -3.79 | 30.35 | 42 |

# 5
# Discussion

*Standing dead trees in Malinau Research Forests (North Kalimantan)*

*(picture by Andes Hamuraby Rozak)*

## 5.1 Discussion

While specific discussions have been done at the end of each chapter of this thesis, the following chapter will discuss the major findings of this thesis in a broader context.

### 5.1.1 Commercial logging and forest C stocks

In Chapter 3, we have shown that commercial wood harvest has a long-lasting and significant influence on total C stocks. We found a difference of 95 Mg C $ha^{-1}$ between areas logged at low versus high intensity, respectively <2% and >20% of initial biomass lost. Logging was found to still significantly affect three main carbon pools 16 years after harvesting: $AGC_{>20}$, $BGC_{>20}$, and deadwood stocks. These three C pools represented on average 70% of the total C stocks and their spatio-temporal variability was mainly explained by logging intensity (Table 3-1, Chapter 3). Our results confirmed the importance of logging intensity in shaping post-logging AGC dynamic and recovery (Piponiot et al. 2016; Rutishauser et al. 2015). Regarding soil carbon stocks that remain poorly assessed in terrestrial carbon accounting studies, logging intensity also had a significant effect on SOC concentration up to 30 cm.

The influence of logging intensity on C stocks was divided into three groups based on the direction of the effect: negative, neutral, and positive. A negative influence was found on $AGC_{>20}$, $BGC_{>20}$, SOC stocks, and total C stocks; a positive influence was found on deadwood stocks; while no influence was detected on $AGC_{5-20}$, $BGC_{5-20}$, and litter stocks. Let's now assume that logging intensity is the sole variable explaining C stocks and all other variables are at state conditions, then our model (see Chapter 3) predicts that increasing logging intensity from 20% (average logging intensity in FSC-certified concessions in East Kalimantan, Indonesian[2]) to 35% (upper bound of typical conventional logging intensity[3]) would reduce $AGC_{>20}$, $BGC_{>20}$, and SOC stocks by 11%, 13%, and 2%, respectively, and increase deadwood stocks by 36% (Figure 5-1).

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[2] Griscom et al. (2014:925) report a typical value of 30 $m^3$ $ha^{-1}$ for FSC-certified concessions in East Kalimantan, Indonesia, equivalent to 20% initial biomass lost (logging intensity = 0.0053*volume harvested + 0.0384 at MRF (E. Rutishauser, unpublished data)).

[3] Ruslandi et al. (2017:106) report a typical value of 50-60 $m^3$ $ha^{-1}$ for conventional logging in Kalimantan, Indonesia, equivalent to 30-35% initial biomass lost.

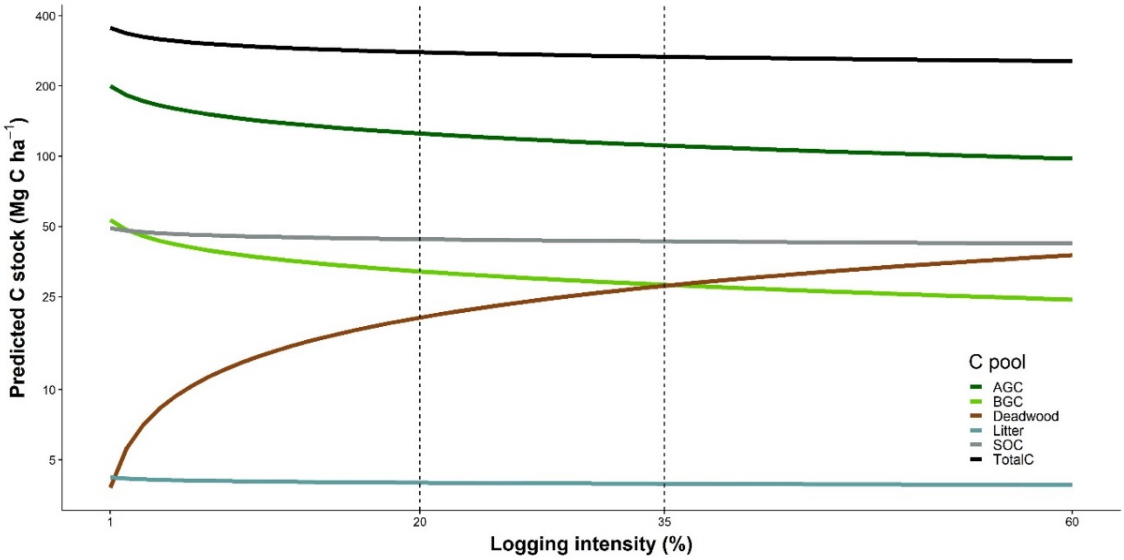


*Figure 5-1 The value of C stocks (Mg C ha$^{-1}$) 16 years following logging predicted from the linear models presented in Chapter 3. Logging intensity 1% (of the pre-logging biomass lost) is assumed as unmanaged or logged at low intensity, 20% is assumed as the typical logging intensity employed in Indonesian production forests, and 35% is assumed as a high logging intensity.*

Overall, an intensification of forest harvest, as currently tested in Indonesia (Ruslandi, Cropper Jr., and Putz 2017), up to 35% of initial biomass removed would result in a decrease of c. 12 Mg C ha$^{-1}$ in 16 years or approx. 0.8 Mg C ha$^{-1}$ yr$^{-1}$. This value is equal to approx. 30% of net C emission of commercial logging in East Kalimantan, Indonesia (Griscom, Ellis, and Putz 2014). Extrapolated to the 0.3 million ha of Indonesian Borneo forests logged annually (Gaveau et al. 2014), this would result in an approx. 0.24 million Mg C yr$^{-1}$ (or approx. 0.9 Tg $CO_2$e yr$^{-1}$) emissions, ~3% of what is emitted annually in the country from logging (Pearson, Brown, and Casarim 2014). This coarse calculation illustrates how the intensification of silviculture in the remaining Bornean forests may impact C emissions at national level.

### 5.1.2 Towards an optimal logging intensity in Dipterocarp forests

The maximum allowable cut, i.e. the maximum number of trees allowed to be harvested per area, has long been discussed in Indonesian production forests (Sist and Nguyen-Thé 2002; Sist et al. 1998; Sist, Picard, and Gourlet-Fleury 2003; Sist, Sheil, et al. 2003). These studies mainly focused on how felling intensities employed in Reduced-Impact Logging (RIL) and conventional logging (CVL) affect forest damage. In Berau (East Kalimantan), Sist et al. (1998) reported that RIL can reduce forest damage by 50% compared to CVL, but only when RIL is implemented under a felling intensity below 8 trees ha$^{-1}$. Over this threshold, the amount of incidental damages is comparable between RIL and CVL techniques. Similar results were reported in Malinau (North Kalimantan) i.e. when RIL employed with >8 trees harvested ha$^{-1}$, both stand damage and canopy disturbance in RIL were comparable with those recorded in CVL under low and moderate intensities (<8 trees ha$^{-1}$) (Sist, Sheil, et al. 2003). Assuming that

(i) a typical harvested tree equal 3.5 Mg C (equivalent to a *Dipterocarpus* of 80 cm DBH) and (ii) forests biomass stocks averages 200 Mg C $ha^{-1}$, a 20% logging intensity, or 15% of biomass harvested, is equivalent to 8 typical trees harvested per hectare. Our study corroborates previous suggestions to use 8 trees as an upper limit to maintain high C stocks in production forests.

### 5.1.3 Towards refined estimates of C stocks in logged forests

The REDD+ initiative aims to reduce C emission from deforestation and forest degradation (Gibbs et al. 2007; Hein et al. 2018). Pearson et al. (2017) reported that the total global annual C emissions of the tropical forests from deforestation and forest degradation reached 8.3 Gt $CO_2$e $yr^{-1}$ of which timber harvesting contributed around 1.1 Gt $CO_2$e $yr^{-1}$ (or approx. 13% of the total C emissions). This calculation might still be an underestimation of reality. Such studies aggregating values at large scale often rely on generic default factors (DF), generally based on the sole measure of AGC (Chapter 1, Table 1-1). For instance, Pearson and collaborators used a default value of 6% of AGC to estimate CWD stocks. Applying this value at our site results in a significant underestimation (paired t-tests, all $P < 0.05$) of deadwood ($n = 28$ samples, mean value = 17.7 Mg C $ha^{-1}$) and litter ($n = 28$ samples, mean value = 4 Mg C $ha^{-1}$) stocks measured in the field (Figure 5-2). In unmanaged or in forests logged at low logging intensity, deadwood stocks estimated through expansion factor are 170% higher than values measured in the field. In high logging intensity, the underestimation falls 55%. For litter stocks, the use of expansion factor underestimates the stocks by, on average, 57%.

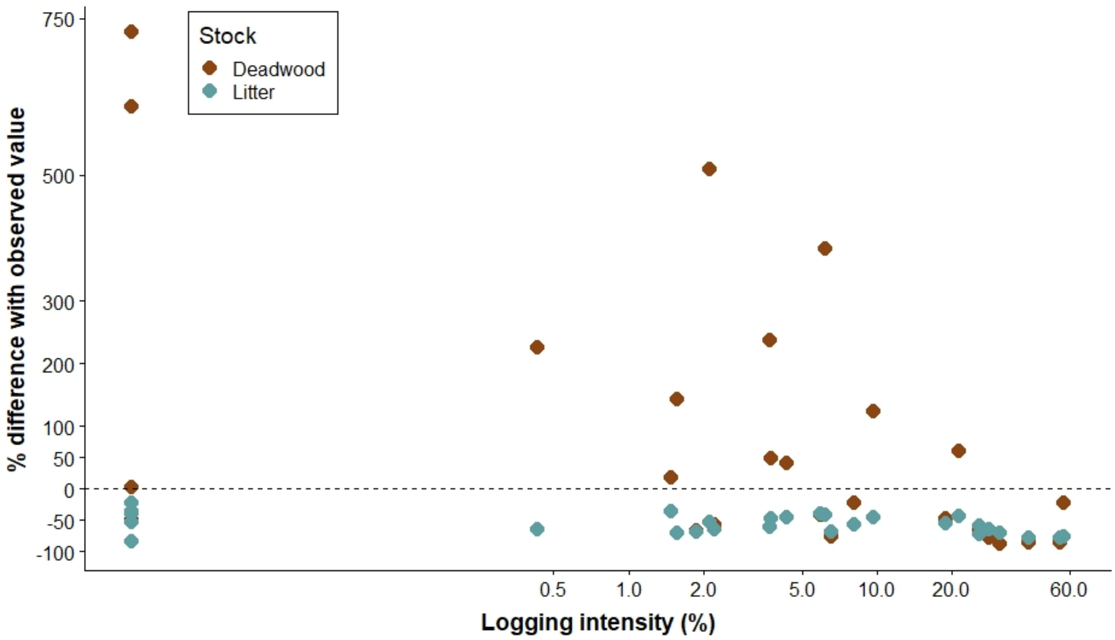


*Figure 5-2 Percentage of the difference of deadwood (A) and litter (B) stocks estimated through a default factor (UNFCCC (2015) relative to the observed values (n=28 subplots).*

In high logging intensity plots, summing up CWD and litter estimated through DF with other C pools results in 13% lower total C stocks (224.7 Mg C $ha^{-1}$ versus 256.2 Mg C $ha^{-1}$, respectively using the expansion factor and measured in the field, $t(3) = 4.7$, $P = 0.02$, Figure 5-3B). We conclude that expansion factors should be used with caution in logged forests, and direct measurement should be preferred for site specific studies when logging intensity and amount of deadwood are high.

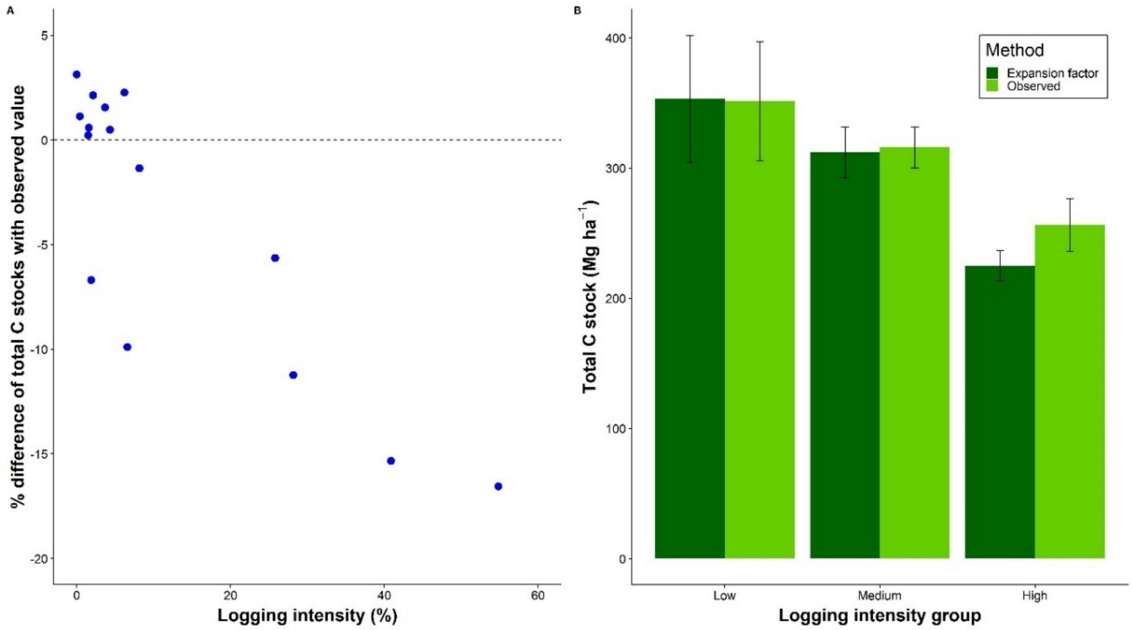


*Figure 5-3 Percentage of the difference of total C stocks estimated through expansion factor relative to observed values (A) and the comparison of total C stocks when deadwood and litter C stock are estimated by direct measurement and the use of default factor in each logging intensity group (B). Logging intensity was grouped into 3 classes i.e. unmanaged or logged at low intensity (0-2% of initial biomass lost), medium intensity (2-20%), and high intensity (>20%). The error bars in Panel B indicate one standard error of the mean of each logging intensity group.*

The underestimation of deadwood and litter stocks when applying default factor in forests with high variability of deadwood is not surprising, as DF assume a positive correlation between AGC and deadwood stocks. However, as revealed by our study, deadwood was found inversely correlated with AGC (linear model, $\beta = -0.12$, Adj. $R^2 = 18\%$, $P = 0.01$). This shift in C allocation is not properly captured by EF that were likely developed for unmanaged forests.

As a lot of effort in estimating forest carbon stocks are put in remotely sensed techniques (Le Toan et al. 2011; Scipal et al. 2010) using gross approximation based on AGC (e.g. Englhart, Keuck, and Siegert 2011; Réjou-Méchain et al. 2015; Coomes et al. 2017), precise information on total C stocks are still needed to reduce uncertainties. Field measurement and data on C stocks in logged and disturbed forests remain rare.

Despite deadwood, litter and SOC account for only 18-32% of total C stocks, a small change in either pool could have a major impact on forest C budgets (Cox et al. 2000; Crowther et al. 2016; Houghton 2003). Here, we have estimated that a 20% decrease of initial AGC could decrease SOC stocks by approx. 5 Mg C $ha^{-1}$ and increase deadwood stocks by approx. 20 Mg C $ha^{-1}$. Extrapolated to 18 million ha of Bornean logged forests, total C emissions from soil and deadwood decomposition could have emitted respectively up to 90 and 360 Tg C over the past 16 years.

### 5.1.4 Commercial logging and forest resilience

The results of our study, particularly on AGC and deadwood stocks (Chapter 3), indicate that high logging intensity (>20%) might lower both forest resilience and resistance compared to low or medium intensities (<20%). By definition, Holling (1973) defined resilience as "the capacity of ecosystems to return to the pre-conditions following a perturbation", while resistance is defined as "the capacity of the ecosystem to absorb disturbances and remain largely unchanged". In Amazonian forests, the capacity of AGC to return to the pre-logging depends on logging intensity. Rutishauser et al. (2015) reported that logging intensity of 10, 25, or 50% would require 12, 43, and 75 years, respectively, to recover initial AGC stocks. In Dipterocarp forests, Pinard and Cropper (2000) predicted that 120 years would be required to approach the pre-logging level of AGC under RIL techniques with an harvesting intensity of 125 $m^3$ $ha^{-1}$ (~33% of initial AGB stocks). In our study, 16 years after logging, $AGC_{>20}$ stocks in forest logged at medium (176 Mg C $ha^{-1}$) and low intensity (193 Mg C $ha^{-1}$) were comparable. The same was found for total C stocks (316 and 351 Mg C $ha^{-1}$ medium and low intensity logging respectively). In contrast, forests logged at higher intensity (>20% of the pre-logging AGC lost) showed a significant reduction of 27% of total carbon stocks.

Beyond the direct reduction of C stocks, logged forests might also become less resilient to ongoing climate changes. High intensity felling affects canopy openness which in turn increases light in the stand and stimulates the growth of the pioneer tree species, such as *Macaranga* or *Mallotus* (Cannon et al. 1994; Primack and Lee 1991; Sist and Nguyen-Thé 2002). These two species were reported to be abundant in logged Dipterocarp forests, being a good indicator of the intensity of disturbance (Slik, Kessler, and van Welzen 2003). A model simulated by Pinard and Cropper (2000) found that the density of pioneers peaked 10 to 40 years after logging. However, these two taxa are sensitive to drought due to a shallow root system and low wood density (Slik 2004). Shallow root systems prevent plants to reach deeper soil water during droughts (Nepstad et al. 1994), making them more prone to die. In addition, low wood density (e.g. average *Macaranga* wood density = 0.38 g $cm^{-3}$) tree species are generally more prone for cavitation during droughts, suffering elevated mortality (Hacke et al. 2001; Greenwood et al. 2017). Therefore, increasing abundance of pioneer species due to high logging intensity in logged forests makes them less resistant to drought (Markesteijn et al. 2011; Condit, Hubbell, and Foster 1995; Hérault and Piponiot 2018; Bonal et al. 2016). For instance, Slik (2004) found that a major drought event that hit Bornean forests in 1997/1998 led to an additional tree mortality of 11%, 18%, and 23%, in undisturbed, old-logged, and recently logged forests respectively. Interestingly, 65% of all dead trees encountered in logged forest plots pertained to the genus *Macaranga,* a common pioneer species in Southeast Asia. More generally, drought was found to increase tree mortality (Phillips et al. 2010; Nakagawa et al. 2000; Lingenfelder and Newbery 2009; Van Nieuwstadt and Sheil 2005) especially among the largest trees (Bennett et al. 2015; Potts 2003) that encompass most C in the forest (Sist et al. 2014; Slik et al. 2013). Since logging took place at our study site (1999), Bornean forests experienced prolonged droughts (characterized by below normal October precipitation) in 2002, 2004, 2006, and 2009 (Chen et al. 2016). Further researches are needed to understand the vulnerability of logged forest to climate change, and especially the role in sequestering or emitting C in a near future.

### 5.1.5 Contextualizing the findings to sustainable forest management

Sustainable forest management (SFM) is a broad concept in order to ensure forest sustainability. The aim is to achieving a sustainable production of timber while maintaining other forest attributes necessary to support local livelihoods, biodiversity conservation, and production of ecosystem services (Nasi and Frost 2009; Wilkie, Holmgren, and Castaneda 2003; Kuusipalo, Kangas, and Vesa 1997; Diaz-Balteiro and Romero 2004; Zimmerman and Kormos 2012). Throughout our study, we found that logging affects C stocks over at least 2 decades (Chapter 2, Chapter 3). Focusing AGC stock, no difference in AGC stocks were found between unmanaged plots and 16 years old-logged plots (Table 3-4) where RIL was employed with <20% logging intensity. However, considering commercial AGC timber recovery, we still have a lack of study on how AGC of commercial timber in Bornean forests recovered. A model done by Sist et al. (2003) showed that for Indonesian Dipterocarp forests, a 40 years cycle with 8 trees harvested ha$^{-1}$ was the best option to preserve both the ecological integrity of the forest, ensure yield and economic sustainability. A more recent model developed by Ruslandi et al. (2017) showed that a 50 years rotation with enrichment planting of commercial timber is needed to reach its pre-logging timber volume. Indeed, RIL, as employed in MRF, has been found to decrease forest damage compared to CVL (Sist and Nguyen-Thé 2002; Sist, Sheil, et al. 2003) and therefore might increase both forest resilience and resistance including AGC of commercial tree. However, RIL alone does not necessarily stimulate the growth of Future Crop Trees (FCTs) and might lowered forest resilience and resistance when high logging intensity employed in the forests. To maintain and increase both forest resilience and resistance, some silvicultural treatments such as liana cutting and liberation of FCTs from competing trees through girdling and soil scarification in felling gaps might be considered (Peña-Claros et al. 2008; Fredericksen and Putz 2003; Lussetti et al. 2016; de Graaf, Poels, and Van Rompaey 1999). As an example, Lussetti et al. (2016) reported that RIL techniques in combination with climber cutting in Bornean forests has increased ingrowth and decreased the mortality of FCTs (such as Dipterocarp species), while the ingrowth and growth of pioneer species were lowered.

Another intervention to assure the sustainability of timber production in logged forests consist in planting targeted commercial tree species (Lamb, Erskine, and Parrotta 2005; Chazdon 2008). Ruslandi et al. (2017) reported that enrichment of commercial timber species following logging was able to increase timber yield in Kalimantan Dipterocarp forests. However, planting targeted commercial tree is an expensive intervention and therefore result a financial consequence for forest concessionaires. According to Ruslandi et al. (2017) such intervention might only be considered to the areas with good access, gentle terrain, and low stock of commercial timber trees.

Logged forests in Bornean forests that reached 18 million ha as well as 9 million ha of the intact forest that stated as production forest (Gaveau et al. 2014) seem unable to supply the increasing regional timber demand (ITTO 2015). Logged forests may supply part of this need, but should be managed in a what that maintain timber resource on the long-term. Unfortunately, the recent regulation, in this case Indonesian selective cutting and planting system or *Tebang Pilih dan Tanam Indonesia* (TPTI), set up a cutting cycle of 30 years (Kementerian Kehutanan 2009; Kementerian Kehutanan 2014), likely insufficient to assure the sustainability for future harvests in Indonesia. Some technical guidelines (Sist, Fimbel, et al. 2003), silvicultural treatments (Peña-Claros et al. 2008; Lussetti et al. 2016), or forest restoration (Harrison, Swinfield, and others 2015) might increase the ecological sustainability of production forests including the recovery of AGC of commercial trees but future research is still needed to make sure logged forest is sustained after the first harvest.

## 5.2 Another future research direction

### 5.2.1 Analyzing the relationship between C stocks and biodiversity

Discussion on the relationship between above-ground C stocks (AGC) and biodiversity have been pronounced elsewhere in the tropics (e.g. Beaudrot et al. 2016; Deere et al. 2018; Häger and Avalos 2017; Shen et al. 2016; Sullivan et al. 2017). On a global scale, Sullivan et al. (2017) found that there was a weak positive relationship between AGC and tree diversity indices but only within 1 ha scale. Our preliminary results seem in accordance with Sullivan's study where tree diversity indices (either rarefaction or Shannon-Wiener indices) were weakly correlated with AGC (adj. $R^2$ <50%, Figure 5-4). However, to our knowledge, no such study has been done to analyze the relationship between tree diversity and total C stocks in a managed forest. AGC might weakly correlated with tree diversity, but how deadwood, litter, and SOC stocks correlated with the indices still understudied. Deadwood stocks might correlate with tree diversity because its decomposition rate was depending on their species (Hérault et al. 2010; Zhou et al. 2007). Litter stocks might also depend on the species composition. Yeong et al. (2016) found that leaves on three Dipterocarp species in Bornean forests were decomposed differently with leaves of a light-demanding species. They found that leaves of a light-demanding species (*Parashorea malaanonan*) decomposed faster than a shade-tolerant species (*Hopea nervosa*). Further, with regard to SOC stocks, its stocks were affected by litter decomposition (Zhou et al. 2015) and litter input (Sayer et al. 2011). The combination of those C pools (AGC-BGC, deadwood, litter, and SOC stocks) is therefore hypothesized to be correlated with species diversity. Future studies must be done in order to analyze the relationship between total C stocks and tree diversity at the sub-national scale because the implementation of carbon conservation schemes occurs at this scale. If the study found there is a positive relationship between tree diversity and C storage this means that C oriented conservation strategies will automatically conserve high tree diversity in the forest, vice versa. Furthermore, future studies should also consider how tree diversity recovered following logging and how they affect C stocks. Therefore, the correlation between logging intensity, tree diversity recovery, and C stocks will be revealed.

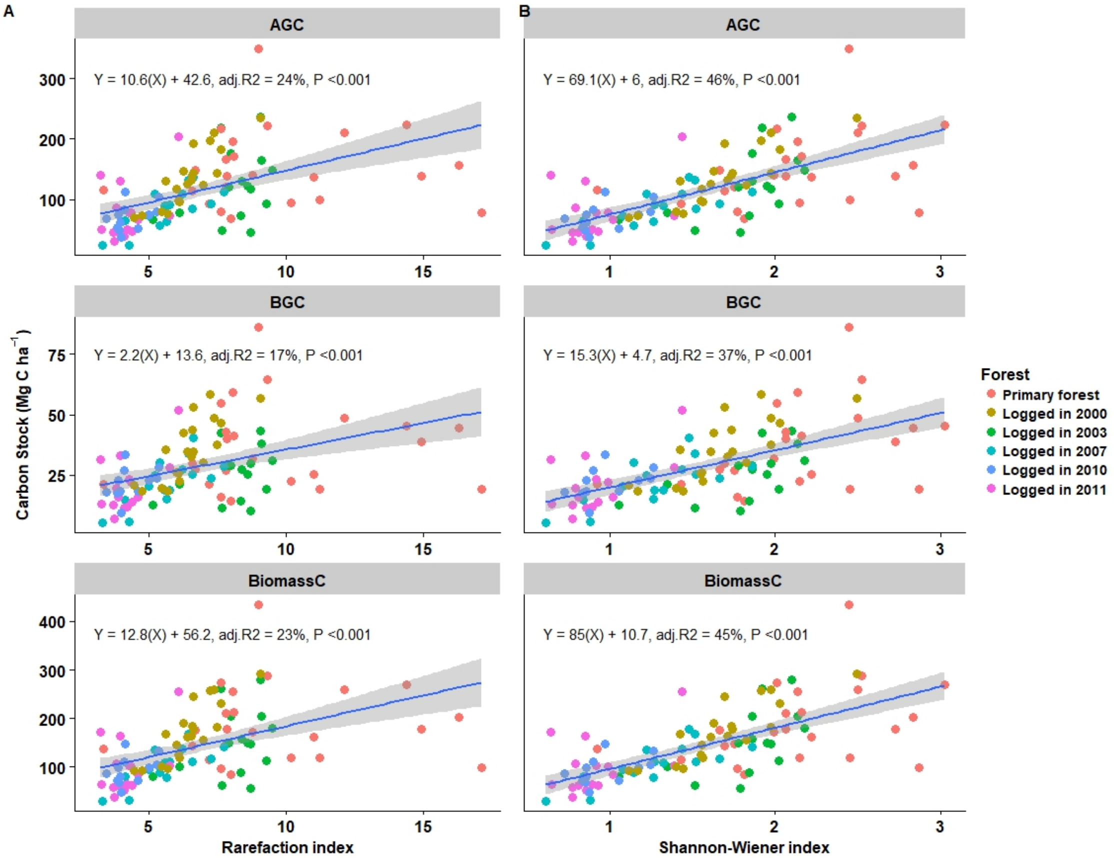


*Figure 5-4 Linear models between species rarefaction index (A) and Shannon-Wiener index (B) on AGC, BGC, and total C in tree biomass. The solid blue line is a linear model with 95% confidence interval.*

# 6

# Summary and conclusion

*A buttress of Shorea sp. (Berau, East Kalimantan)*

*(Picture by Andes Hamuraby Rozak)*

This thesis addressed one main hypothesis and one main question. A total of 8 specific questions were addressed in Chapter 2, 3, and 4. The summaries of those points were presented below.

## Chapter 2

**Rationale:** Selective logging consists in harvesting a few large trees per hectare that once felt generates patches of incidentally killed trees. Capturing this heterogeneity and patchy pattern at the landscape scale is challenging. The following are the answer to the research questions addressed in this study:

a. ***What is the variability of C stocks in logged forests under different time since logging?***
   Total C stocks in the different time since logging were ranged from 130 to 174 Mg C ha$^{-1}$ (Figure 2-5). The forest that experienced logging recently (logged in 2010) has lower C stocks (130 Mg C ha$^{-1}$), followed by forests logged in 2007 (140 Mg C ha$^{-1}$), and 2003 (174 Mg C ha$^{-1}$).
b. ***Do LIS and FAS serve equally to predict deadwood stocks in logged forests?***
   Our study has demonstrated that LIS and FAS returned relatively similar sampling variance (Table 2-2). The indication was shown by the almost similar sampling variance ($S^2$) between LIS and FAS when the stocks were predicted through decay classification. Considering sampling variance and bias for these methods, we have shown that FAS method simultaneously with decay classification (calibrated locally) was found more efficient than LIS method.
c. ***What is the minimum sampling unit to accurately estimate deadwood stocks in logged forests?***
   Using FAS and decay classification, we have estimated that 39% and 12% sampling intensities from the total examined forest area are needed to estimate the average deadwood stocks with an error of 5 and 10%, respectively (Table 2-4).

## Chapter 3

**Rationale:** Selective logging is known to reduce AGB while increasing deadwood through collateral damages. By opening large canopy gaps, logging also affects litter production and change microclimates locally which in turn affects organic matter input to the soil. The degree of forest damage, as well as C recovery, was shown to be related to logging intensity. Evaluating the effect of logging intensity and other environmental variables on C stocks were the main focus of this study. The following are the answer to the research questions addressed in this study.

a. ***What are the variability and the proportion of C pools in logged forests under different logging intensities?***
   In this chapter, we have shown that total C stocks were ranged from 218 to 554 Mg C ha$^{-1}$ (Figure 3-1). In low logging intensity group (0-2%) total C stocks were 351 Mg C ha$^{-1}$, followed by medium intensity (2-19%) that reached 316 Mg C ha$^{-1}$ and high intensity

(19-57%) that reached 256 Mg C ha$^{-1}$ (Figure 3-3). Furthermore, with regard to the proportion of each C pool to total C stocks, we found the proportion of C stored in living trees reached 82%, followed by SOC stocks (14%), deadwood (3%) and litter (1%) in low logging intensity group. In medium logging intensity group, C stocks in living trees reached 80% of the total C stocks, followed by SOC stocks (15%), deadwood (4%), and litter 1%). While in high logging intensity group, living C trees represent 68% of total C stocks, followed by SOC stocks (17%), deadwood (13), and litter (2%).

***b. What is the main driver of C stocks in MRF?***

Our study has demonstrated that logging intensity was found to be the sole variable explaining the variabilities of $AGC_{>20}$, $BGC_{>20}$, deadwood, and total C stocks (Table 3-1). The other C pools i.e. litter C stocks were influenced by slope and clay content, and SOC stocks were influenced by nitrogen content in the soil.

***c. How does logging intensity influence each C pool and total C stocks?***

This thesis has demonstrated that logging intensity indeed has an influence on C stocks (Table 3-1). In a specific result, $AGC_{>20}$, $BGC_{>20}$, and total C stocks were negatively affected by logging intensity, while, deadwood stocks were positively affected by logging intensity.

## Chapter 4

**Rationale:** The removal of a few large trees through selective logging leads to the reduction of AGB and litter production. While microclimates change locally and might accelerate litter and organic matter decomposition, logging is therefore expected to affect soil organic matter. Evaluating the effect of logging on SOC stocks is therefore important. The following are the answer to each research question addressed in this study.

***a. What are the variability and the main factor influencing SOC stocks in each layer and each accumulated layer?***

This study has shown that SOC stocks in each layer and each accumulated layer were highly variable (Figure 4-2). Total SOC stocks were ranged from 40 to 52 Mg C ha$^{-1}$ with an average of 46 Mg C ha$^{-1}$. About 30 Mg C ha$^{-1}$ of the total SOC stocks (approx. 65%) were found only in the upper 30 cm layer. Thus, the variabilities of SOC stocks for layer 0-5, 5-15, and 15-30 cm were explained by slope but in conjunction with other variables (Table 4-1). While for the accumulated layer, each variable has its own contribution explaining the variabilities of SOC stocks (Table 4-2). For example, four variables (i.e. logging intensity, clay content, litter C stocks, and slope) were found explaining the variability of SOC stocks for 0-100 layer.

**b.** ***How do logging intensities influence SOC stocks in each layer and each accumulated layer?***

This study has demonstrated that logging intensity was found as a variable explaining SOC stocks in the following layer: 5-15 cm, 0-15 cm, 0-30 cm, and 0-100 cm (Figure 4-4). However, those layers were not influenced solely by logging intensity but with other variables such as slope (layer 5-15), clay content and available phosphorus (layer

0-15 cm), clay content and slope (layer 0-30 cm), and clay content, litter C stocks, and slope (layer 0-100 cm). Based on our model (the model coefficient, β), all SOC stocks mentioned above were negatively influenced by logging intensity.

**In conclusion**, this study has demonstrated that the hypothesis if logging still has an influence on C stocks has been confirmed. We have found that logging intensity solely explained the variabilities of $AGC_{>20}$, $BGC_{>20}$, deadwood, and total C stocks 16 years after logging (Chapter 3, Table 3-1). We have also found that SOC stocks were also influenced by logging intensity but in conjunction with the other variables (Chapter 4, Table 4-2). Therefore, we have confirmed that logging, particularly logging intensity, drives forest C stocks. Furthermore, we have also confirmed the specific hypothesis that the higher logging intensity, the less total C stocks in the forests (Chapter 3, Figure 3-3A). Due to their impact on forest C balance, we therefore recommend to limit logging intensity less than 20% of biomass removal or equivalent to maximum 8 trees harvested per hectare.

# Résumé substantiel

# Vers une meilleure estimation des stocks de carbone dans les forêts exploitées à Diptérocarpées de Bornéo

*La canopée de forêt de Diptérocarpée (Berau, Kalimantan du l'Est)*

*(Photo par Andes Hamuraby Rozak)*

# Introduction

## Forêts tropicales et cycles du carbone

Alors que les forêts tropicales ne représentent que 15% de la surface terrestre mondiale (Keenan et al. 2015), on estime qu'elles abritent plus de la moitié des espèces connues dans le monde (Dirzo and Raven 2003a; Wright 2005). Elles fournissent également des fonctions sociétales et environnementales importantes, telles que la production de bois (Keller et al. 2007; Sasaki, Chheng, and Ty 2012), la régulation du climat (e.g. Bawa and Markham 1995; Bonan 2008) ainsi que le cycle des éléments nutritifs et du carbone (C) (e.g. Baccini et al. 2017; Le Quéré et al. 2018; Malhi 2012; Qie et al. 2017; Vitousek and Sanford 1986). Les arbres sont la caractéristique la plus emblématique des forêts tropicales, formant une interface subtile entre le sol et l'atmosphère. Grâce à la photosynthèse, les arbres séquestrent le C dans leur tronc, leurs branches et leurs feuilles (également connu sous le nom de biomasse aérienne, AGB), et la biomasse souterraine (BGB) dans les racines. Lorsque les arbres meurent, la biomasse se décompose lentement (Hérault et al. 2010; Chambers et al. 2000) et forme d'importants stocks de bois mort (Pfeifer et al. 2015; Osone et al. 2016). Alors que la plus grande partie de cette matière organique est réémise dans l'atmosphère, une petite fraction pénètre dans les sols et enrichit les stocks de C organique du sol (SOC). Résumer le C stocké dans ces différents bassins à l'échelle du paysage place les forêts tropicales parmi les écosystèmes les plus riches en C (Pan et al. 2011). En effet, on estime que les forêts tropicales stockent c. 250 Gt C dans les arbres vivants (Saatchi et al. 2011) et représentent 40 Pg C $an^{-1}$ (ou 35%) de la productivité primaire brute terrestre (Beer et al. 2010).

En dépit de tous les avantages apportés par les forêts tropicales, ces dernières continuent à disparaitre ou à se dégrader à un rythme élevé en raison des activités anthropiques (Achard et al. 2014; Baccini et al. 2017; Potapov et al. 2017). Selon Hansen et al. (2013), les forêts tropicales contribuent à 30% de la perte de couverture forestière mondiale avec une perte annuelle de forêts de 0,2 million d'ha au cours de la période 2000-2012. Les causes immédiates de la déforestation sont la combinaison de l'expansion agricole et de l'expansion des infrastructures (Geist and Lambin 2002; Lambin et al. 2001). En plus de la déforestation, les forêts tropicales sont dégradées par la récolte du bois, les feux incontrôlés et le bois de chauffage / charbon de bois (Hosonuma et al. 2012). Ensemble, la conversion des forêts en agriculture, la foresterie et la dégradation des forêts sont responsables d'un peu moins d'un quart des émissions anthropiques de gaz à effet de serre (IPCC 2014).

L'agriculture, la foresterie et l'utilisation des terres (AFOLU) ont contribué de manière significative aux émissions de gaz à effet de serre durant la période 1970-2010 (IPCC 2014). En 2010 en particulier, l'AFOLU représentait 25% (environ 12 Tg d'équivalent $CO_2$) des émissions anthropiques totales annuelles. Pour 2007-2016, les émissions de C attribuables à l'utilisation des terres, au changement d'affectation des terres et à la foresterie ont été estimées à 1,3 Gt C $an^{-1}$ ou environ. 10% des émissions mondiales de C (Le Quéré et al. 2018). Les émissions issues de la déforestation et de la dégradation des forêts (y compris l'exploitation forestière) représentent respectivement 70% et 30% des pertes de AGC dans les forêts tropicales (Baccini et al. 2017) mais varient régionalement. Par exemple, en Asie tropicale, on estime que la dégradation des forêts du secteur forestier représente jusqu'à 45% des émissions totales de C émises annuellement dans la région, dont 50% sont dues aux activités d'exploitation forestière.

Pour lutter contre les émissions de C dues à l'AFOLU, le programme REDD a été initié en 2007 par les parties à la Convention Cadre des Nations Unies sur les Changements Climatiques (UNFCCC) (Hein et al. 2018; Hein and van der Meer 2012). Le REDD+ est un faisceau d'actions qui favorise la gestion durable des forêts (SFM), la conservation et la mise en valeur des stocks de C forestier. Le REDD+ bénéficie d'incitations financières dans les pays capables d'empêcher l'exploitation ou la conversion des forêts tropicales en des utilisations plus lucratives des terres. Un concept clé réside dans la gestion durable des forêts (SFM), définie comme «le processus de gestion des forêts pour atteindre un ou plusieurs objectifs de gestion clairement définis en vue de produire un flux continu de produits et services forestiers souhaités sans réduction indue de ses valeurs intrinsèques et sa productivité future et sans effets indésirables indus sur l'environnement physique et social » (ITTO 2005). Il a été démontré que la SFM présente plusieurs avantages par rapport aux pratiques d'exploitation conventionnelles, notamment en matière de réduction des émissions de carbone. Par exemple, passer de l'exploitation conventionnelle (CVL) à une exploitation forestière à impact réduit (RIL) dans les forêts tropicales de production pourrait réduire les émissions de C de 30-50% (environ 1,5-2,1 Gg $CO_2$ $an^{-1}$) tout en maintenant le niveau de production (environ 166-280 $m^3$ de bois d'utilisation finale) dans un cycle de 50 ans (e.g. Sasaki et al. 2016; Sasaki, Chheng, and Ty 2012). Malheureusement, RIL n'est pas largement employé par l'industrie forestière et a toujours ses propres défis à résoudre (tels que la capacité technique et l'application de la réglementation dans chaque pays) afin d'atteindre l'objectif de la SFM en particulier dans les forêts tropicales de production (Nasi and Frost 2009; Putz, Sist, et al. 2008; Schulze, Grogan, and Vidal 2008).

## Sur l'importance des forêts exploitées

Les forêts de production désignent les forêts principalement destinées à la production de bois, de fibres, de bioénergie et / ou de produits forestiers non ligneux (FAO 2010). Dans les régions tropicales, la sélection de quelques espèces commerciales est la pratique dominante (Putz, Sist, et al. 2008; Sist, Garcia-Fernandez, and Fredericksen 2008; Sist, Fimbel, et al. 2003). En 2010, environ la moitié des forêts tropicales restantes étaient destinées à la production de bois (environ 400 millions d’hectares sur un total de 780 millions d’hectares de forêts tropicales permanentes, Blaser et al. 2011). De 2005 à 2010, la superficie des forêts de production dans les régions tropicales a augmenté de 50 millions d'hectares. Récemment, les forêts exploitées et secondaires sont devenues une caractéristique de plus en plus importante des paysages tropicaux et représentent maintenant la majorité du couvert forestier restant dans de nombreuses régions. Si plusieurs études ont souligné l'importance de ces forêts dans le maintien de la fonction et des services écosystémiques (Edwards, Tobias, et al. 2014), notamment dans le maintien de la biodiversité (e.g. Edwards et al. 2011; Edwards, Magrach, et al. 2014; Costantini, Edwards, and Simons 2016) et affectant les stocks de C (e.g. Martin et al. 2015; Sist et al. 2014; Khun and Sasaki 2014a), les caractéristiques fonctionnelles et écologiques des forêts de production sont modifiées.

En effet, l'exploitation commerciale affecte directement les stocks de C grâce à la récolte directe de grandes tiges et/ou à la destruction d'arbres non ciblés (c'est-à-dire des dommages indirects). En créant de grands espaces dans la canopée, les microclimats changent localement (Gaudio et al. 2017; Hardwick et al. 2015) et accélèrent la décomposition des déchets (Salinas et al. 2011) et la matière organique du sol (Covington 1981; Fontaine et al. 2004; Raich et al. 2006). Dans les forêts tropicales africaines, Chiti et al. (2015) ont signalé que les niveaux de C organique du sol jusqu'à une profondeur de 100 cm étaient fortement affectés par l'exploitation forestière et que les forêts continuaient à perdre du C aprés de nombreuses années (45 ans après l'exploitation forestière). Alors que dans les forêts amazoniennes, Berenguer et al. (2014) ont rapporté deux résultats contrastés de SOC jusqu'à une profondeur de 30 cm, soit (1) à Paragominas (Amazonie brésilienne), les stocks étaient plus élevés dans les forêts exploitées (63 Mg C ha$^{-1}$) que dans les forêts intactes (43 Mg C ha$^{-1}$); à Santerém, toujours en Amazonie brésiliene, les stocks étaient comparables entre les forêts exploitées (55 Mg C ha$^{-1}$) et les forêts intactes (57 Mg C ha$^{-1}$).

Il a été démontré que l’ampleur des dommages causés à la forêt, ainsi que la vitesse de récupération du C, étaient principalement liés à l'intensité de l'exploitation forestière (Piponiot et al. 2016; Rutishauser et al. 2015; Sist, Sheil, et al. 2003; Sist and Nguyen-Thé 2002). La biomasse aérienne se reconstitue au fil du temps grâce à la croissance des arbres survivants, et le recrutement de nouveaux arbres et dépend de l'intensité de l'exploitation forestière (Rutishauser et al. 2015). Cependant, même si l’AGC augmente avec la croissance des arbres après la coupe, elle ne compensera peut-être pas la mortalité retardée des arbres blessés et peut entraîner une diminution de l’ AGC pendant plusieurs années après l’exploitation (Shenkin et al. 2015). Ainsi à Lusetti et al. 2016 ont observé un taux de mortalité des arbres élevé juste après la coupe, puis une diminution de ce taux jusqu'à 10 ans, puis une nouvelle augmentation entre 10 et 18 ans (Lussetti et al. 2016). En ce qui concerne la récupération de l’AGC, Rutishauser et al. (2015) ont estimé que les pertes de 25% d'AGC de pré-exploitation nécessiteraient environ 43 ans pour récupérer ses stocks aux stocks AGC initiaux dans les forêts amazoniennes. L'exploitation forestière devrait également augmenter les stocks de bois mort en raison des dommages collatéraux consécutifs à l'exploitation forestière (Figure 1-1). Pour le bois mort, ce stock diminuera avec le temps en raison de la décomposition, mais le taux de décomposition dépend des espèces et de leur diamètre (Harmon et al. 1995; Hérault et al. 2010). Par conséquent, l'apport de bois mort dépend principalement de la mortalité naturelle et de la mortalité des arbres après l'exploitation forestière.

Les forêts tropicales peuvent être soit une source, soit un puit de C selon la manière dont elles sont gérées. Lorsqu'elles sont exploitées ou gérées, les forêts tendent à devenir une source nette tout en revenant à la normale après quelques décennies (Blanc et al. 2009). Cependant, la dynamique de C à long terme dans les forêts gérées dépend de plusieurs variables telles que les techniques d'exploitation forestière (Pinard and Cropper 2000; Sasaki et al. 2016; Sasaki, Chheng, and Ty 2012), l'intensité de l'exploitation (Piponiot et al. 2016; Rutishauser et al. 2015), et des facteurs environnementaux (Vieira et al. 2004; Piponiot et al. 2016). Comprendre la reconstitution des stocks de C et l'équilibre à long terme du C dans les forêts aménagées est fondamental pour attester leur contribution environnementale et sociale et éviter leur conversion.

## Évaluation des stocks de C dans les forêts tropicales

Selon une recherche avec un opérateur booléen (comme expliqué dans la Figure 1-2), soixante-neuf études évaluant les stocks de C dans les forêts tropicales ont été trouvées. Les forêts exploitées représentent environ un tiers (25 études) de toutes les études. Trente deux études sont situées en Amérique tropicale. En général, les stocks totaux de C (AGC, BGC, bois mort, litière et SOC) dans les forêts intactes sont plus élevés que ceux des forêts exploitées, sans tenir compte de l'intensité de l'exploitation forestière et du temps écoulé depuis l'exploitation forestière. La différence moyenne est seulement d'environ 20 Mg C ha$^{-1}$ (340 et 320 Mg C ha$^{-1}$ dans la forêt intacte et exploitée, respectivement). La Figure 1-2C montre que les principaux stocks de Carbone (AGC et BGC) sont plus élevés dans les forêts intactes, mais que les stocks de bois mort sont plus faibles que dans les forêts exploitées. En conséquence, les proportions moyennes de AGC par rapport aux stocks totaux de C sont plus élevées dans les forêts intactes que dans les forêts exploitées (55% contre 43%, respectivement) et inversement pour la proportion de bois mort (10% contre 25%, respectivement). Les pools de C sont très variables parmi les types de forêts, en particulier les stocks de bois mort (Figure 1-2C). Cette variabilité s'explique probablement par les différences de régime de gestion (telles que l'intensité de la récolte ainsi que les techniques d'exploitation forestière) et les conditions environnementales (telles que le climat et les sols).

La plupart des études sur les stocks de Carbone visent à comparer des stocks particuliers de C ou de C totaux entre les forêts exploitées et non exploitées, ou en comparaison avec d'autres types d'utilisation des terres telles que les forêts secondaires ou les plantations d'huile de palme (Table 1-1). De plus, la plupart des études sur les stocks de C ne tiennent pas compte de l'intensité de l'exploitation forestière comme variable testée dans leurs études bien que cette variable soit le principal facteur influençant les dégâts dus à l'exploitation et le rétablissement du C (Piponiot et al. 2016; Rutishauser et al. 2015; Sist and Nguyen-Thé 2002). Il est donc nécessaire de raffiner et de comprendre tous les stocks de C ayant des intensités d'exploitation variables dans les forêts gérées ou exploitées. Cependant, quantifier les stocks de C dans les forêts exploitées est difficile parce que le processus de croissance et de mortalité, la production de litière, les stocks de bois mort et les stocks de SOC sont difficiles à évaluer avec un système satellitaire (Houghton, Hall, and Goetz 2009). Même si une technique de télédétection plus avancée sera lancée vers 2020 dans le cadre de la mission BIOMASS (Le Toan et al. 2011; Scipal et al. 2010), cette mission inclut uniquement la biomasse aérienne, à l'exclusion des autres stocks de carbonequi contribuent pour environ 35% du stock total C (Saner et al. 2012). De plus, les données précises concernant l'historique de l'exploitation forestière et notamment l'intensité de coupe restent encore très peu nombreuses et seuls quelques dispositifs expérimentaux, dont celui de cette étude, dispose de ces informations capitales. Par conséquent, cette étude comblera cette lacune et donnera de nouvelles perspectives sur l'effet à long terme de l'intensité de l'exploitation forestière sur les principaux réservoirs de carbone d'une forêt aménagée.

## Vue d'ensemble des forêts de Bornéo

L'île de Bornéo est la plus grande île d’'Asie du Sud-Est et est partagée entre 3 pays à savoir l’Indonésie, la Malaisie et le Brunei. En 2010, la superficie forestière incluant les forêts aménagées et intactes représentait environ 53% de la surface totale de l'île (Gaveau et al. 2014) (Figure 1-3). Les forêts de Bornéo comme dans toute la région sont dominées par la famille des Dipterocarpacées. Les Dipterocarpacées sont une famille parmi les plus grands arbres trouvés dans les forêts de plaines de Bornéo (Appanah and Turnbull 1998; Ashton 1983; Banin et al. 2012; Whitmore 1984). La famille rassemble environ 695 espèces (Christenhusz and Byng 2016) dont 267 à Bornéo (Ashton 1983; Brearley, Banin, and Saner 2016; Whitmore 1984). Ce taxon est la famille la plus dominante de l'île suivie par les Euphorbiacées avec 22% et 12% de tous les arbres (DHP ≥ 9,8 cm), respectivement (Slik et al. 2003). En raison de sa dominance à la fois en termes de tiges (jusqu'à 25% de la densité totale des arbres) et de surface terrière (souvent 50% de la surface terrière totale), les forêts dominées par les Dipterocarpacées sont appelées forêts mixtes de Diptérocarpacées (Whitmore 1984). Les genres Shorea et le Dipterocarpus sont les plus abondants (Slik et al. 2003).

La plupart des forêts de Bornéo sont soumises à des pressions intenses et sont sous la menace des activités anthropiques telles que l'exploitation forestière et la conversion à la monoculture et à l'industrie minière (Gaveau et al. 2014; Nasi and Frost 2009; Sodhi et al. 2009; Wilcove et al. 2013). Ces activités ont un impact négatif sur la biodiversité de l'Asie du Sud-Est (Sodhi et al. 2009) et le régression des forêts intactes (Gaveau et al. 2014) qui sont essentiels pour la conservation de la biodiversité (e.g. Barlow et al. 2007; Gibson et al. 2011; Hughes, Daily, and Ehrlich 2002). Au cours de la période 1973-2010, les forêts indonésiennes de Bornéo ont perdu environ 30% ou l'équivalent de 12,4 millions d'hectares. Gaveau et al. (2014) ont identifié environ 21 millions d'hectares de forêts intactes, dont 8,8 millions d'hectares (environ 42% des forêts intactes) appartiennent à la classe d'utilisation des terres de production forestière et sont susceptibles d'être exploitées dans un proche avenir et 3,4 millions (16% des forêts intactes) susceptibles d’être convertis à d'autres utilisations des terres (Table 1-1). En supposant que toutes les forêts de production sont exploitées et que les zones destinées à la conversion sont converties, les forêts exploitées constitueront la principale classe d'utilisation des terres de l’île avec 26,8 millions d'hectares (environ 36% de la superficie totale) suivies par les forêts intactes avec 8.8 millions d'hectares (environ 16% de la superficie totale). Les forêts de production joueront donc un rôle crucial à la fois dans la production de biens (bois, rotin, nourriture, etc.) et le maintien des stocks de Carbone, de la biodiversité et la production de nombreux autres services environnementaux clés (Meijaard and Sheil 2007; Sist et al. 2015). Bien que les zones protégées de l'île couvrent environ 6,6 millions d'hectares (Proctor, McClean, and Hill 2011), ces zones sont aussi touchées par la déforestation et la dégradation des (Curran et al. 2004).

Cette étude se concentre sur la compréhension de l'impact à long terme de l'intensité de l'exploitation forestière sur cinq stocks de C dans les forêts de production de Bornéo. A Bornéo, les données de suivi à long terme après exploitation des stocks de carbone sont rares car il existe peu de sites expérimentaux dans les forêts exploitées (Sist et al. 2015). Ainsi dans la partie indonésienne de Bornéo, il n'existe que deux sites expérimentaux de suivi de la dynmaique forestière avant et après exploitation :: STREK (à Berau, Kalimantan de l'Est, voir Bertault and Kadir 1998) et les parcelles MRF (à Malinau, Kalimantan Nord, voir CIFOR and ITTO 2002). Cependant, la plupart des données ne concernent que les arbres vivants, alors que le bois mort, la litière et le C organique du sol font toujours défaut. Bien que ces trois réservoirs de C représentent des stocks et une proportion faibles des stocks de C total (Saner et al. 2012), ils peuvent avoir une contribution importante dans les émissions de C à l'échelle régionale ou mondiale et peuvent donc avoir un impact significatif sur l'avenir de la concentration atmosphérique de $CO_2$ (Houghton 2012; Houghton, Byers, and Nassikas 2015). A titre d'illustration, une faible perte de 2 Mg C ha-1 du sol dans les forêts exploitées entraînera une perte d'envion. 36 Tg C (1 Tg = $10^6$ tonnes) provenant des forêts exploitées de Bornéo.

## Pratiques d'exploitation forestière à Bornéo

Les forêts mixtes de diptérocarpées à Bornéo ont longtemps été exploitées pour la production de bois (Nasi and Frost 2009; Nicholson 1979), malheureusement avec une mauvaise mise en œuvre des pratiques de gestion. Dans les années 1990, deux directives d'exploitation forestière innovantes, publiées par l'Organisation internationale des bois tropicaux (ITTO 1992) et la FAO (1999) ont été diffusés afin de promouvoir des pratiques de gestion durable des forêts (FAO 2016). Dans le même temps, avec la prise de conscience croissante concernant l'importance de préserver les forêts tropicales, l'Indonésie et la Malaisie sont allées plus loin en développant leurs propres directives pour compléter les directives de l'ITTO. En Indonésie notamment, des recherches approfondies sur la réduction des dégâts forestiers et la minimisation des effets de l'exploitation forestière ont été menées à Berau (Kalimantan du Est) et suivies à Malinau (Kalimantan du Nord, anciennement Kalimantan Est) (Sist, Sheil, et al. 2003; Sist et al. 1998; Sist and Nguyen-Thé 2002). Les études ont démontré que les techniques de RIL sous une intensité d'exploitation forestière modérée (8 arbres récoltés $ha^{-1}$) pourraient réduire les dégâts d'exploitation de manière significative. Sist et al. (1998) ont rapporté que le RIL réduisait les dégâts de 50% par rapport à l'exploitation forestière conventionnelle à Berau, mais les dégâts dépendaient de l'intensité de l'exploitation forestière. En outre, dans le cas des forêts de production malaisiennes, Pinard et Putz (1996) ont rapporté qu'un an après l'exploitation, les forêts exploitées par le RIL ont 67% de la biomasse pré-exploitation comparativement aux exploitations conventionnelles avec 44% de la biomasse pré-exploitation. En ce qui concerne les stocks de C, Putz et al. (2008) ont indiqué que l'utilisation de pratiques d'exploitation à faible impact conserverait au moins 0,16 Gt C par an et serait supérieure d'au moins 30 Mg $ha^{-1}$ à celles qui sont exploitées de façon conventionnelle (Pinard and Cropper 2000; Pinard and Putz 1997). Sur la base de modèles de dynamique du carbone dans les forêts de Diptérocarpées, Pinard et Cropper (2000) ont rapporté que plus de 60 ans après une RIL, la moyenne du carbone total stocké dans la forêt était supérieure de 36 Mg C ha$^{-1}$ à celle exploitée de façon conventionnelle. Suite à de nombreuses autres études sur le RIL, ces techniques d'exploitation ont été largement reconnues comme la condition de base pour prétendre à une gestion durable des ressources forestières en forêt tropicale (Elias et al. 2001; Sist, Garcia-Fernandez, and Fredericksen 2008).

L'exploitation des forêts des basses terres de Bornéo sera toujours une activité de routine pour au moins deux raisons. La première raison est que les secteurs de l'industrie forestière continueront toujours à satisfaire la demande de bois qui augmente avec le temps (ITTO 2015). À titre d'exemple, la consommation de bois est passée de 271 millions de m$^3$ (2012) à 275 millions de m$^3$ (2014) dans le monde. La deuxième raison est que les secteurs de l'industrie forestière représentent une source de revenu importante pour les pays en développement (Berry et al. 2010; Miles and Kapos 2008), comme l'Indonésie (environ 2,6 milliards USD) et la Malaisie (3,7 milliards USD) qui produisent environ. 41% du bois rond du marché mondial du bois (FAO 2016). Cependant, les bénéfices de contribution aux revenus des pays ont augmenté plus lentement (Lebedys and Li 2014). Les forêts exploitées subissent une autre pression pour être converties à d'autres utilisations plus rentables comme la plantation d'huile de palme et l'agriculture (Sodhi et al. 2004).

# Objectif, question de recherche et hypothèse

L'objectif principal de cette étude est d'évaluer l'effet à long terme de l'exploitation forestière sur les cinq principaux stocks de carbone. Les objectifs spécifiques de l'étude étaient les suivants :

a. Estimer la variabilité des stocks de C, en particulier des stocks de biomasse aérienne et souterraine des arbres, de bois mort et de litière au-dessus du sol, à différents temps d'intervalle après exploitation au sein d'un concessionnaire certifié à Berau, Kalimantan du Est (chapitre 2),
b. Comparer l'efficacité de l'estimation du bois mort à l'aide des méthodes d'échantillonnage à surface fixe (FAS) et d'échantillonnage par intersection (LIS) simultanément avec la classification de la décomposition du bois (3 classes) et le pénétromètre dynamique pour estimer chaque densité spécifique de bois mort (chapitre 2),
c. Estimer la variabilité des stocks totaux de C et évaluer le principal facteur influençant chaque stock de C et les stocks totaux de C sous différentes intensités d'exploitation dans le MRF 16 ans après l'exploitation (chapitres 3 et 4)

Pour atteindre cet objectif, la motivation sous-jacente de cette thèse basée sur les considérations discutées ci-dessus est de répondre à la question principale : dans quelle mesure l'intensité de l'exploitation forestière affecte-t-elle chaque stock de C et les stocks totaux de C. Plus précisément, cette étude aborde les questions de recherche spécifiques suivantes :

Chapitre 2. Estimation de la variabilité des stocks de Carbone (AGC, BGC, bois mort et litière) à différents moments depuis l'exploitation et la comparaison de l'efficacité de la méthode d'estimation des stocks de bois mort à Berau (Kalimantan du Est).

a. Quelle est la variabilité des stocks de carbone dans les forêts exploitées à différents moments depuis l'exploitation forestière ?
b. Est-ce que les méthodes LIS et FAS prédisent de façon identique les stocks de bois mort dans les forêts exploitées ?
c. Quelle est l'unité d'échantillonnage minimale pour estimer avec précision les stocks de bois mort dans les forêts exploitées ?

Chapitre 3. Estimation de la variabilité des stocks de C (AGC, BGC, bois mort, litière et SOC) sous différentes intensités d'exploitation forestière et démêlage du conducteur des stocks de C dans la forêt exploitée dans le MRF.

a. Quelle est la variabilité et la proportion de stocks de C dans les forêts exploitées sous des intensités d'exploitation différentes ?
b. Quels sont les principaux facteurs affectant les stocks de C dans le MRF ?
c. Comment l'intensité de l'exploitation influence-t-elle chaque stock de Carbone et les stocks totaux de C ?

Chapitre 4. Évaluation du principal déterminant des stocks de SOC pour chaque couche et chaque couche d'accumulation dans le MRF.

a. Quelle est la variabilité et le principal facteur influençant les stocks de SOC dans chaque couche et chaque couche accumulée ?
b. Comment les intensités d'enregistrement influencent-elles les stocks de SOC dans chaque couche et chaque couche accumulée ?

Sur la base de la question de recherche principale, nos hypothèses sont les suivantes :

a. La biomasse aérienne (AGC) et souterraine (BGC) sont négativement affectés par l'intensité de l'exploitation forestière
b. Le stock de bois mort augmente avec l'intensité de l'exploitation forestière.
c. Le stock total de C est également affecté négativement par l'intensité de l'exploitation forestière.

Par conséquent, l'hypothèse principale de cette étude est que l'exploitation forestière garde une forte influence sur les stocks totaux de Carbone, 16 ans après l'exploitation forestière. L'hypothèse spécifique est que plus l'intensité de l'exploitation est élevée, moins sont les stocks de C dans les forêts. Une hypothèse sur les effets de l'intensité de l'exploitation forestière au fil du temps sur les stocks de C total et la dynamique de chaque bassin de C après l'exploitation forestière est présentée en Figure 1-1.

# Matériel et méthodes

## Zone d`étude

La zone d'étude comprend deux sites : (1) dans une zone de concession forestière certifiée à Berau, Kalimantan du Est (Figure 1-3, boîtes bleues), et (2) dans la Forêt de Malinau au Kalimantan du Nord (Figure 1-3, boîtes blanc). Les deux sites sont dominés par des espèces de *Dipterocarpacées* des genres *Hopea*, *Shorea* et *Dipterocarpus* englobant la plupart des espèces commerciales récoltées dans la région. La topographie du premier site consiste en un paysage vallonné avec des vallées peu profondes et des ravins dont l'altitude maximale est de 140 m au-dessus du niveau de la mer (Arbainsyah et al. 2014). L'altitude du deuxième site varie de 100 à 300 m avec des pentes de 10 à 70%. Le deuxième site, également connu sous le nom de placettes permanentes de Cifor-Cirad, était le site expérimental établi en 1998 sur la gestion durable des forêts, l'utilisation intégrée des terres, l'exploitation forestière à impact réduit, la biodiversité dans les forêts productives et l'aspect culturel et social de l'exploitation forestière (CIFOR and ITTO 2002). Les peuplements du deuxième site étaient parmi les forêts indonésiennes les plus diversifiées avec 205 espèces d'arbres inventoriées sur 1 ha de la parcelle d'échantillonnage permanente (Sheil et al. 2010).

## Mesure des stocks de C à Berau, Kalimantan du Est

La méthodologie de l'étude a été héritée d'une étude antérieure sur l'effet de l'exploitation forestière sur la diversité des espèces (Arbainsyah et al. 2014). Nous avons repris les transects préexistants mis en place par cette étude à l'exception du site d’exploitation datant de 2010 mis en place par nous-même. Cinq transects parallèles, espacés de 50 m, ont été miss en place et divisés en sections carrées de 100 m de côté. Quatre sites d'étude, ont été sélectionnés en fonction du temps écoulé depuis l'exploitation forestière : forêt non exploitée, forêt exploitée en 2003, 2007 et 2010 soit 12, 8 et 5 ans après l'exploitation forestière. Chaque site couvre une superficie de 300 m x 200 m avec une zone tampon de 10 m des deux côtés, totalisant 6,6 ha par site.

Deux zones de 20 m x 300 m ont été utilisées pour l'inventaire des arbres. Tout arbre (DHP ≥ 10 cm) dans cette zone est identifié par le parabotaniste et mesuré à 130 cm de hauteur (DHP) ou 50 cm au-dessus de tout contrefort ou déformation. Pour la mesure du bois mort, une méthode d'échantillonnage à zone fixe (FAS) a été utilisée (Figure 2-1, carrés bleus). Un échantillon de FAS se composait de 3 quadrats de 10 m x 10 m situés au hasard de chaque côté de chaque ligne de transect, c'est-à-dire un quadrat par section de 100 m de la ligne de transect. Alors qu'un échantillon de LIS était constitué d'une ligne de transect de 100 m. Les procédures LIS suivent une méthode expliquée par Van Wagner (1968). Tous les bois morts abattus et debout d'un diamètre ≥ 10 cm situés dans un quadrat FAS donné ont été mesurés. Alors que dans LIS seulement le bois mort tombé est considéré. Pour le bois mort tombé, nous avons suivi le protocole de la tronçonneuse où tous les bois morts tombés qui se situent dans le quadrat sont mesurés (Gove and Deusen 2011). Pour le bois mort debout, le diamètre à 130 cm (DHP) et la hauteur (à l'aide d'un télémètre laser ou d'un ruban à mesurer) ont été enregistrés dans la mesure du possible. La densité de bois mort est évaluée à l'aide de trois classes basées sur une classification visuelle (Walker et al. 2014). Simultanément, la densité de bois mort a également été mesurée pour chaque bois mort trouvé dans les quadrats en utilisant un pénétromètre qui montre une classification plus objective que celle de la décomposition (Larjavaara and Muller-Landau 2010). De plus, les stocks de litière ont été échantillonnés et pesés dans un petit quadrat de 1 m x 1 m (Figure 2-1, boîtes noires) incluant du bois mort d'un diamètre < 10 cm.

## Mesure des stocks de C à MRF, Kalimantan du Nord

L'étude des stocks de C, couvrant 5 principaux stocks de carbone, à savoir la biomasse aérienne, la biomasse souterraine, le bois mort, la litière et le stock de carbone organique du sol, a été réalisée à Malinau Research Forests (MRF), Kalimantan Nord (Figure 1-3, boîte blanche). Les stocks de C ont été quantifiés dans 28 parcelles de 0,25 ha dans le MRF avec différentes intensités d'exploitation forestière. Dans notre étude, l'intensité de l'exploitation forestière (%) a été définie comme la proportion de biomasse perdue après exploitation au premier recensement post-exploitation par rapport au stock de biomasse pré-exploitation. Cette proportion variait entre 0 et 57%. Chaque stock de C a été estimé en utilisant une méthode standard. L'AGB a été estimée à l'aide d'une équation allométrique pantropicale mise à jour par (Chave et al. 2014) La biomasse souterraine (BGB) a été estimée à l'aide d'un modèle allométrique développé dans les forêts de Diptérocarpées (Niiyama et al. 2010). Les stocks de bois mort ont été estimés en utilisant la méthode FAS testée à Berau et les stocks de litière ont été estimés et calculés sur la base de la masse de litière sèche provenant de l'échantillon de litière recueilli à 1 mx 1 m dans le FAS (pour le bois mort). Enfin, les stocks de Carbone du sol (SOC) ont été estimés jusqu'à une profondeur de 1 m, où la teneur en carbone organique a été estimée en utilisant la méthode de combustion humide (Walkley and Black 1934).

# Résultats et discussion

## Résumé des résultats

Pour structurer le contexte des résultats, il est nécessaire de répondre à l'hypothèse et de réexaminer les questions de recherche mentionnées au chapitre 1. Cette thèse a porté sur une hypothèse principale et une question principale. Au total, 8 questions spécifiques ont été traitées dans les chapitres 2, 3 et 4. Les résumés de ces points ont été présentés ci-dessous.

**Questions de recherche au chapitre 2 :**

a. ***Quelle est la variabilité des stocks de carbone dans les forêts exploitées à différents moments depuis l'exploitation forestière ?***
   Les stocks totaux de carbone à différents temps après exploitation variaient de 130 à 174 Mg C ha$^{-1}$ (Figure 2-5). Les forêts qui ont récemment été exploitées (2010) ont des stocks de C plus faibles (130 Mg C ha$^{-1}$), suivi des forêts qui ont été exploitées en 2007 (140 Mg C ha$^{-1}$), et 2003 (174 Mg C ha$^{-1}$).
b. ***Est-ce que LIS et FAS servent également à prédire les stocks de bois mort dans les forêts exploitées ?***
   Notre étude a démontré que LIS et FAS ont donné une variance d'échantillonnage relativement similaire (Table 2-2). L'indication a été montrée par la variance d'échantillonnage presque similaire ($S^2$) entre LIS et FAS lorsque les stocks ont été prédits par la classification de la désintégration. Considérant la variance d'échantillonnage et le

biais de ces méthodes, nous avons montré que la méthode FAS associée à la classification de désintégration (calibrée localement) était plus efficace que la méthode LIS.

c. ***Quelle est l'unité d'échantillonnage minimale pour estimer avec précision les stocks de bois mort dans les forêts exploitées ?***

   En utilisant la classification du FAS et de la désintégration, nous avons estimé que 39% et 12% d'efforts d'échantillonnage de la surface forestière totale examinée sont nécessaires pour estimer les stocks moyens de bois mort avec une erreur de 5 et 10% (Table 2-4).

**Questions de recherche au chapitre 3 :**

a. ***Quelle est la variabilité et la proportion des compartiments de stock de Carbone dans les forêts exploitées sous différentes intensités d'exploitation forestière ?***

   Sur ce chapitre, nous avons montré que les stocks totaux de C variaient de 218 à 554 Mg C $ha^{-1}$ (Figure 3-1). Dans le groupe de faible intensité d'exploitation (0-2%), le stock total de C était en moyenne de 351 Mg C $ha^{-1}$, 316 Mg C $ha^{-1}$ et 256 Mg C $ha^{-1}$ dans les parcelles à faible, moyenne et forte intensité respectivement. Dans le groupe de parcelles à faible intensité d'exploitation, la proportion de C stocké dans les arbres vivants était de 82%, suivie des stocks de SOC (14%), de bois mort (3%), et la litière (1%). Dans le groupe d'intensité d'exploitation moyenne, les stocks de C dans les arbres vivants représentaient 80% des stocks totaux de C, suivis des stocks de SOC (15%), de bois mort (4%), et la litière 1%). Enfin, dans le groupe d'intensité d'exploitation, les stocks de C des arbres vivants représentaient seulement 68% des stocks totaux de carbone, suivis par les stocks de SOC (17%), le bois mort (13%), et la litière (2%).

b. ***Quel est le principal moteur des stocks de C dans MRF ?***

   Notre étude a démontré que l'intensité de l'exploitation forestière était la seule variable expliquant les variabilités des $AGC_{>20}$, des $BGC_{>20}$, du bois mort et des stocks de C total (Table 3-1). Les autres compartiments, c'est-à-dire les stocks de litière, ont été influencés par la pente et la teneur en argile ; et les stocks de SOC ont été influencés par la teneur en azote dans le sol.

c. ***Comment l'intensité de l'exploitation influence-t-elle chaque pool de C et chaque stock de C ?***

   Cette thèse a démontré que l'intensité d'exploitation a en effet une influence sur les stocks de C. Dans un résultat spécifique, les stocks $AGC_{>20}$, $BGC_{>20}$ et C totaux ont été négativement affectés par l'intensité de l'exploitation, tandis que les stocks de bois mort ont été positivement affectés par l'intensité de l'exploitation forestière.

**Questions de recherche au chapitre 4 :**

a. ***Quelle est la variabilité et le principal facteur influençant les stocks de SOC dans chaque couche et chaque couche accumulée ?***

   Cette étude a montré que les stocks de SOC dans chaque couche et chaque couche accumulée étaient très variables (Figure 4-2). Les stocks totaux de SOC variaient de 40 à 52 Mg C $ha^{-1}$ avec une moyenne de 46 Mg C $ha^{-1}$. Sur 30 Mg C $ha^{-1}$ des stocks totaux de SOC (environ 65%) ont été trouvés seulement dans la couche supérieure de 30 cm. Ainsi, les variabilités des stocks de SOC pour les couches 0-5, 5-15 et 15-30 cm ont été expliquées par la pente mais en conjonction avec d'autres variables. Alors que pour la couche accumulée, chaque variable a sa propre contribution expliquant les variabilités des stocks SOC. Par exemple, quatre variables (l'intensité de l'exploitation forestière, la teneur en argile, les stocks de litière C et la pente) ont été trouvées pour expliquer la variabilité des stocks de SOC pour la couche 0-100.

b. ***Comment les intensités d'exploitation influencent-elles les stocks de SOC dans chaque couche et chaque couche accumulée ?***

Cette étude a démontré que l'intensité d'exploitation avait une influence sur la teneur en Carbone des horizons suivants : 5-15 cm, 0-15 cm, 0-30 cm et 0-100 cm (Table 4-1,Table 4-2). Cependant, d'autres variables ont également une influence comme par exemple la pente pour l'horizon 5-15 cm, la teneur en argile et le phosphore disponible pour l'horizon couche 0-15 cm, la teneur en argile et la pente (horizon 0-30 cm), et la teneur en argile, les stocks de litière C et la pente pour l'ensemble de l'horizon 0-100 cm. Sur la base de notre modèle (le coefficient du modèle, β), tous les stocks de SOC mentionnés ci-dessus ont été influencés négativement par l'intensité de l'exploitation forestière.

## Discussion des résultats

Les discussions spécifiques ont été menées dans chaque chapitre de cette thèse. Cependant, il est nécessaire de discuter des principaux résultats inclus dans cette thèse. En ce qui concerne nos résultats, les éléments suivants sont particulièrement intéressants :

a. Discussion méthodologique sur l'estimation des stocks de bois mort
b. Le rôle à long terme de l'intensité de l'exploitation forestière sur les stocks de C forestier
c. L'évaluation du facteur d'expansion pour estimer les stocks de bois mort et la litière
d. L'analyser la relation entre les stocks de C et la biodiversité

*Discussion méthodologique sur l'estimation des stocks de bois mort*

Le bois mort intéresse les forêts exploitées de façon sélective, car l'exploitation forestière génère une grande quantité de débris et d'arbres morts soit autour des arbres récoltés ou le long de la piste de débusquage. Nous avons démontré que ses stocks représentent environ. 13,5% du total des stocks de C dans le groupe des grandes intensités (chapitre 3). Afin d'estimer les stocks de bois mort, nous avons évalué la précision et l'efficacité des deux méthodes communément utilisées, à savoir la méthode d'échantillonnage par intersection (LIS) et la méthode d'échantillonnage à surface fixe (FAS). Notre étude a montré que le LIS a estimé en moyenne 20% plus élevé que la méthode FAS (chapitre 2). Ces résultats élevés de LIS par rapport à FAS ont également été signalés dans la forêt amazonienne intacte (Baker et al. 2007). Baker et al (2007) ont rapporté que la masse de bois mort tombé estimée par LIS était 24 Mg $ha^{-1}$, alors que le FAS a eu 14 Mg $ha^{-1}$ ou environ. 42% de surestimation par rapport au FAS. Une autre étude dans un type différent d'écosystème (i.e. dans la rivière) faite par Warren et al. (2008) a également rapporté une constatation similaire selon laquelle LIS surestimait le volume de bois mort d'environ. 15% par rapport à la méthode de recensement.

Les différences entre LIS et FAS étaient dues à plusieurs raisons. Alors que le LIS renvoie des estimations non biaisées du bois mort, les résultats du FAS sont affectés de plusieurs sources de biais, c'est-à-dire le biais dû aux erreurs de non-détection et le biais dû à l'estimation du volume de bois mort. L'erreur de non-détection du bois mort sera vraisemblablement minime en raison de la petite taille de notre sous-placette (10 m x 10 m), tandis que la dernière, l'erreur de l'estimation est inconnue lorsqu'elle est appliquée à une population particulière de bois mort. En outre, il convient de noter que LIS a trois hypothèses de base (Van Wagner 1968): (a) les morceaux de bois mort sont cylindriques ; (b) tous les morceaux de bois mort sont horizontaux ; et (c) les morceaux de bois mort sont orientés au hasard.

Par conséquent, en raison des hypothèses et de certaines conditions telles que discutées par Ringvall et Stahl (1999), la méthode LIS introduira également une erreur (Van Wagner 1968). Le LIS sera optimal si les transects sont placés au hasard (Kaiser 1983), ce qui est le cas de notre plan d'échantillonnage, c'est-à-dire la ligne de transect parallèle. Des études plus approfondies doivent être réalisée pour déterminer l'arrangement optimal de la ligne de transect, tel que discuté dans les études précédentes (Bell et al. 1996; Gregoire and Valentine 2003; Hazard and Pickford 1986). En effet, le LIS est plus simple et facile à mettre en œuvre sur le terrain, cependant, LIS ne prend en compte que le bois mort tombé, ce qui n'est pas le cas du FAS, c'est-à-dire capable de mesurer et estimer le bois mort. En raison des limites de l'étude, avantages/inconvénient, et compte tenu des biais résultant des deux méthodes, nous concluons que le FAS associé à la classification de décomposition (pour estimer la densité spécifique de bois mort) est recommandé et peut être un bon compromis pour estimer efficacement les stocks de bois mort dans les forêts exploitées Bien que la méthode FAS soit intrinsèquement biaisée, sur la base de notre simulation, l'intensité d'échantillonnage de 12% de la surface totale étudiée est suffisante pour estimer les stocks de bois mort avec une erreur de 10%.

*Le rôle à long terme de l'intensité de l'exploitation forestière sur les stocks de C forestier*

Au chapitre 3, nous avons démontré que l'intensité de l'exploitation forestière a toujours une influence sur les stocks de C, en particulier sur les $AGC_{>20}$, les $BGC_{>20}$ et les stocks de bois mort. Ces trois bassins de C représentaient en moyenne 70% des stocks totaux de C. En raison de leurs proportions, il n'était pas surprenant que l'intensité de l'exploitation influence également les stocks totaux de C 16 ans après l'exploitation forestière. Sur ces stocks de C, l'intensité de l'exploitation forestière a été utilisée comme une seule variable expliquant leurs variabilités. Notre résultat, en particulier sur AGC, était en accord avec d'autres études réalisées dans les forêts amazoniennes qui ont rapporté que l'intensité de l'exploitation agi comme la principale variable explicative sur la dynamique AGC (Piponiot et al. 2016; Rutishauser et al. 2015). En outre, en utilisant différentes variables telles qu'utilisées au chapitre 3, les stocks de SOC (couche 0-100) ont également été influencés par l'intensité de l'exploitation mais avec d'autres variables, notamment la teneur en argile, les stocks de litière et la pente. C'est donc l'intensité de l'exploitation qui joue encore un rôle crucial dans l'équilibre du C dans les forêts 16 ans après l'exploitation forestière.

L'influence de l'intensité de l'exploitation forestière sur les stocks de C a été divisée en trois groupes en fonction de leur coefficient dans nos modèles linéaires présentés au chapitre 4, c'est-à-dire négatif, neutre et positif. L'influence négative a été détectée sur les $AGC_{>20}$, les $BGC_{>20}$, les stocks de SOC et les stocks de C totaux ; l'influence positive a été trouvée sur les stocks de bois mort ; tandis que l'influence neutre a été détectée uniquement pour les stocks de litière. En supposant que l'intensité de l'exploitation soit la seule variable expliquant les stocks et les autres variables à l'état, selon notre modèle, l'augmentation de l'intensité d'exploitation de 1 à 20% réduira les $AGC_{>20}$, $BGC_{>20}$ et SOC de 37%, 40%, et 10%, respectivement (Figure 5-1). Alors que pour le bois mort, l'augmentation de l'intensité de l'exploitation forestière à 20% augmentera ses stocks 4 fois comparativement à 1% de l'intensité de l'exploitation forestière. Globalement, en combinant tous les bassins C 16 ans après l'exploitation forestière, les stocks totaux de C diminueront de 21% lorsque l'intensité de l'exploitation augmentera de 1 à 20% de la perte initiale de biomasse. Dans des informations plus pratiques, en supposant que l'exploitation avec la technique RIL a contribué à 25% des dommages forestiers (Sist and Nguyen-Thé 2002), par conséquent, une intensité d'exploitation forestière de 20% équivaut à 15% de la perte de biomasse uniquement à partir des arbres récoltés. Avec les hypothèses (1) la moyenne de la masse arborescente individuelle 3.5 Mg C (par exemple *Dipterocarpus* spp.; $\rho$ = 0.61, DHP = 80 cm) et (2) le C moyen de la biomasse dans les forêts non gérées atteint 200 Mg C $ha^{-1}$, ce 15% de la biomasse est donc équivalent à environ. 30 Mg C ou environ. 8 arbres récoltés $ha^{-1}$.

*L'évaluation du facteur d'expansion pour estimer les stocks de bois mort et la litière*

L'initiative REDD+ vise à réduire les émissions de C provenant de la déforestation et de la dégradation des forêts (Gibbs et al. 2007; Hein et al. 2018). Une estimation annuelle de ces émissions C a été rapportée pour les forêts tropicales par Pearson et al. (2017). On a signalé que les émissions annuelles totales de C des forêts tropicales ont atteint 8.3 Gt $CO_2$e $yr^{-1}$ dont la récolte de bois a contribué autour 1.1 Gt $CO_2$e $yr^{-1}$ (ou approx. 13% des émissions totales de C). Cependant, ce rapport pourrait considérablement sous-estimer les résultats. Dans leur étude, un facteur d'expansion UNFCCC (2015) a été utilisé pour estimer les stocks de bois mort et de litière provenant des stocks AGC. Sur la base de nos données (n = 28 sous-parcelles), les stocks de bois mort et de litière ont été significativement différents lorsque le facteur d'expansion a été estimé par rapport aux stocks mesurés (tout $P < 0.05$). L'utilisation du facteur d'expansion a sous-estimé les stocks de bois mort et de détritus de 44% et 58%, respectivement. Par conséquent, nous avons conclu que, afin d'estimer avec plus de précision les émissions de C dans les forêts exploitées, nous devons éviter l'utilisation d'un tel facteur d'expansion.

La sous-estimation des stocks de bois mort et de litière par facteur d'expansion dans la forêt exploitée n'est pas surprenante car les stocks (en particulier de bois mort) dépendent de l'intensité de l'exploitation forestière (chapitre 4). Alors que l'intensité de l'exploitation variait selon les forêts, les stocks de bois mort étaient très variables (Carlson et al. 2016; Osone et al. 2016; Pfeifer et al. 2015). En Indonésie, dans les forêts de Bornéo, Osone et al. (2016) ont rapporté que le rapport du bois mort à AGC variait de 40 à 200% et dépendait de l'intensité de l'exploitation forestière. Alors qu'en Malaisie Bornean forêt, Pfeifer et al. (2015) ont rapporté que le rapport bois mort et AGC variait de 5 à 60% et dépend de leur indice de perturbation. En outre, conformément à ces études, nous avons démontré que les stocks de bois mort étaient positivement corrélés avec l'intensité de l'exploitation forestière. Dans un traitement d'intensité élevée de l'exploitation forestière, les stocks de AGC après exploitation se sont avérés plus faibles que ceux de faible intensité. En revanche, les stocks de bois mort ont été trouvés plus élevés par rapport à la faible intensité de l'exploitation forestière. En raison de cette hypothèse, si nous utilisons le facteur d'expansion, lorsque l'intensité de l'exploitation forestière est élevée dans les forêts, les stocks de bois mort devraient être faibles en raison du faible niveau des stocks AGC, et vice versa. Par conséquent, l'utilisation du facteur d'expansion n'est pas recommandée spécifiquement dans une forêt présentant des variabilités élevées de stocks de bois mort tels que les forêts exploitées.

*L'analyser la relation entre les stocks de C et la biodiversité*

Des discussions sur la relation entre les stocks de C aérien (AGC) et la biodiversité ont été prononcées ailleurs dans le tropique (e.g. Beaudrot et al. 2016; Deere et al. 2018; Häger and Avalos 2017; Shen et al. 2016; Sullivan et al. 2017). À l'échelle mondiale, Sullivan et al. (2017) ont trouvé qu'il y avait une relation positive faible entre les AGC et les indices de diversité des arbres, mais seulement à l'échelle de 1 ha. Nos résultats préliminaires semblent en accord avec l'étude de Sullivan où les indices de diversité des arbres (soit les indices de raréfaction ou de Shannon-Wiener) étaient faiblement corrélés avec AGC (Figure 5-4). Cependant, à notre connaissance, aucune étude de ce genre n'a été réalisée pour analyser la relation entre la diversité des arbres et les stocks totaux de C dans une forêt aménagée. La AGC pourrait être faiblement corrélée avec la diversité des arbres, mais la corrélation entre les stocks de bois mort, de litière et de SOC et les indices n'a pas été suffisamment étudiée. Les stocks de bois mort pourraient être en corrélation avec la diversité des arbres parce que leur taux de décomposition dépendait des espèces (Hérault et al. 2010; Zhou et al. 2007). Les stocks de litière peuvent également dépendre de la composition des espèces. Yeong et al. (2016) ont trouvé que les feuilles sur trois espèces de Diptérocarpée dans les forêts de Bornéo ont été décomposés différemment. Les feuilles d'une espèce exigeante en lumière se sont décomposés plus rapidement qu'une espèce tolérante à l'ombre. De plus, en ce qui concerne les stocks de SOC, ses stocks ont été affectés par la décomposition de la litière (Zhou et al. 2015) et entrée de litière (Sayer et al. 2011). La résultante de ces pools C (AGC-BGC, bois mort, litière et SOC) est donc supposée être corrélée avec la diversité des espèces. Des études futures doivent être effectuées afin d'analyser la relation entre les stocks de C total et la diversité des arbres. Si l'étude révèle une relation positive entre la diversité des arbres et le stockage du C, cela signifie que les stratégies de conservation axées sur le C conservent automatiquement la grande diversité des arbres dans la forêt, et inversement.

# Dansk resumé

# Mod bedre estimater kulstoflagre i de udnyttede Dipterocarp skove på Borneo

*Dødwood i Malinau Research Forests (Nord Kalimantan)*

*(Foto af Andes Hamuraby Rozak)*

# Introduktion

Mens tropiske skove kun udgør 15% af den jordens overflade, anslås de at være hjem for mere end halvdelen af de kendte arter på jorden. De bidrager samtidigt med vigtige samfundsmæssige og miljømæssige funktioner, såsom træproduktion, regulering af klimaet samt næringsstof- og kulstofkredsløb. Træer er det mest symbolske træk ved tropiske skove, og danner en subtil grænseflade mellem jorden og atmosfæren. Gennem fotosyntese binder træerne kulstof i deres stammer, grene og blade (også kendt som overjordisk biomasse, AGB) og underjordisk biomasse (BGB) i rødderne. Når træer dør, nedbrydes biomassen langsomt og danner store lagre af dødt ved. Mens det meste af dette organiske materiale genudledes til atmosfæren, bliver en lille del bundet i jorden og beriger jordens organiske kulstoflagre (SOC). Det samlede kulstoflager i disse forskellige puljer placerer på landskabsskala tropiske skove blandt de mest kulstof rige økosystemer. Faktisk skønnes tropiske skove at lagre c. 250 Gt C i levende træer og tegner sig for 40 Pg C $yr^{-1}$ (eller 35%) af den terrestriske brutto primærproduktion.

Til trods for alle de goder der leveres af tropiske skove, forsvinder eller udtømmes de stadig med høj fart gennem menneskelige aktiviteter. En nylig undersøgelse rapporterede, at tropiske skove bidrager med ca. 30% af den globale afskovning med det årlige skovtab stigende med 0,2 millioner ha år-1 i 2000-2012. De primære årsager til skovrydning er kombinationen af arealanvendelsesændringer til landbrug, hugst og udbygning af infrastruktur. Udover skovrydning forringes de tropiske skove gennem træfældning, ukontrollerede brande og hugst til brug for brænde og trækul. Sammenfattende er konvertering til landbrug, skovdrift og skovforringelse ansvarlig for knap en fjerdel af den menneskabte drivhusgasudledninger. Specielt forventes skovforringelse fra skovbrugssektoren i tropisk Asien at udgøre op til 45% af de samlede kulstofudledninger, der årligt udsendes i regionen, hvoraf 50% skyldes hugst i produktionsskove.

Produktionsskove er skove primært udpeget til produktion af træ, fiber, bioenergi og/eller ikke-skovprodukter. I tropiske områder er udvælgelse af nogle få kommercielle træarter den dominerende praksis. I 2010 var omkring halvdelen af de resterende tropiske skove udpeget til træproduktion. Fra 2005 til 2010 steg området af produktionsskov i tropiske områder med 50 millioner ha. For nylig er afdrevne og sekundære skove blevet et stadig mere fremtrædende træk ved tropiske landskaber og udgør nu hovedparten af det resterende skovareal i mange regioner.

Kommerciel hugst påvirker direkte kulstoflagre gennem direkte høst af store træer og aflivning/beskadigelse af træer af ikke-mål arter (kaldet tilfældig beskadigelse). Ved at skabe store huller i kronelaget ændres mikroklimaet lokalt og fremskynder nedbrydningen af førne og kulstof i jorden (SOC). Graden af skoveforringelse såvel som genopbygningen af kulstoflageret har vist sig primært at være forbundet med hugstintensiteten. Det overjordiske levende kulstoflager (AGC) kan genopbygges over tid gennem fortsat vækst af overlevende og nytilkomne træer, men afhænger af hugstintensiteten. Selvom AGC øges gennem trævækst efter hugst, kan det ikke kompensere for den forsinkede død af tilfældigt beskadigede træer og deraf følgende lavere AGC i løbet af ti år. Derfor er forståelse af den langsigtede kulstofbalance i produktionsskove afgørende for at afdække deres miljømæssige og sociale goder og undgå konvertering.

Hovedformålet med nærværende undersøgelse er at vurdere den langsigtede effekt af hugst på de fem vigtigste kulstoflagre: overjordisk (AGC) og underjordisk (BGC) i levende træer (DBH >5 cm), dødt organisk stof (dødt ved og litter) og kulstof i jorden (SOC). Bag dette formål er den underliggende målsætning for denne afhandling, at svare på hovedspørgsmålet: *i hvilket omfang påvirker skovhugst (dvs. hugstintensitet) hvert kulstoflager og de samlede kulstoflagre i Dipterocarp-skove på Borneo*. Baseret på hovedspørgsmålet forventer vi, at AGC og BGC er negativt korreleret med hugstintensiteten; og mængden af dødt ved positivt korreleret med hugstintensiteten. På grund af den store andel kulstof i levende træer (AGC og BGC) forventer vi, at de samlede kulstoflagre også er negativt korreleret med hugstintensiteten. Derfor er hovedhypotesen for denne undersøgelse, at hugstintensiteten stadig har en indflydelse og stadig spiller en afgørende rolle for de samlede kulstoflagre 16 år efter hugst. Den specifikke hypotese er, at desto højere hugstintensitet, desto mindre kulstoflagre i skovene.

# Metoder

Studieområdet ligger i Malinau Research Forest (MRF) i Nord-Kalimantan. Stedet er domineret af *Dipterocarpaceae* arter, såsom *Hopea spp.*, *Shorea spp.*, og *Dipterocarpus spp.* omfattende de fleste kommercielle arter i regionen. Terrænet varieret fra 100-300 m over havet med 10-70% hældning. Området, også kendt som CIFOR's permanente prøveflader, blev oprettet i 1998 som forsøgsområde for bæredygtig skovforvaltning, integreret arealanvendelse, ekstensiveret skovdrift, biodiversitet i produktionsskov, og kulturelle og sociale aspekt af skovdriften. Forsøgsområderne i MRF er blandt de mest diverse indonesiske skove med 205 træarter registreret på en 1 ha stor permanent prøveflade.

Kulstoflagre blev kvantificeret i 28 0,25-ha prøvefelter inden for MRF med forskellig hugstintensitet. I vores undersøgelse blev hugstintensitet (%) defineret som andelen af biomassetab ved første opgørelse efter hugst ud af biomassen forud for hugst, og varierede fra 0-57%. Biomassetabet svarer til summen af biomassen af udtaget træ og beskadigede træer, som var døde ved første opgørelse efter hugst. Hvert kulstoflager blev estimeret ved anvendelse af en standardmetode. AGB blev estimeret ved hjælp af en opdateret allometrisk ligning for pantropiske skove: $AGB_{est} = exp[-1.803 - 0.976E + 0.976\ln(\rho) + 2.673\ln(DBH) - 0.0299[\ln(DBH)]^2]$ (E = klimavariabel, ρ = specifik trædensitet, DBH = diameter af brysthøjde) der viste sig at være mere præcis end en lokal allometrisk model; BGB blev estimeret ved anvendelse af en allometrisk model udviklet i Dipterocarp skove: $BGB_{est} = 0.023(DBH)^{2.59}$; lagrene i dødt ved blev anslået ved hjælp af opgørelse i 10 m x 10 m plots; førnelagret blev estimeret og beregnet på basis af en tørret prøve af det organiske lag indsamlet i en 1 m x 1 m firkant inden for dødt ved plottene; og SOC-lagrene blev estimeret til 1 m dybde, hvor organisk kulstofindhold blev estimeret ved anvendelse af vådforbrænding. Et standardforhold på 47% blev brugt til at estimere kulstofindholdet i både levende (AGC og BGC) og død biomasse (dødt ved og førne). Levende træer blev desuden opdelt i to grupper baseret på deres DBH: 5-20 cm ($AGC_{5\text{-}20}$ og $BGC_{5\text{-}20}$) og >20 cm ($AGC_{>20}$ og $BGC_{>20}$).

Lineære mixed modeller blev udviklet til at teste forholdet mellem hugstintensitet, topografi (dvs. hældning) og jordvariabler (dvs. lerindhold, nitrogenindhold og tilgængeligt fosfor) for hvert kulstoflager. Med hensyn til SOC-lagre blev også udviklet lineære mixed modeller. De inkluderede hugstintensitet, hældning, lerindhold, tilgængelige fosfor og kulstoflager i førnen som forklarende variabler, og blev testet for hvert lag samt akkumuleret SOC pulje. I begge modeller blev den oprindelige skovstruktur inden for hvert plot medregnet som en random effekt for at reducere rumlig afhængighed.

# Resultater og diskussion

Afhandlingen behandlede en hovedhypotese og et hovedspørgsmål, opsummeret herunder:

**Hovedhypotese: Hugst har stadig en indflydelse og spiller stadig en afgørende rolle på kulstoflagrene 16 år efter hugst.**

Denne undersøgelse har vist, at hypotesen, at hugst stadig har indflydelse på kulstoflagrene, er blevet bekræftet. Vi har konstateret, at hugstintensiteten alene kunne forklare variationerne i $AGC_{>20}$, $BGC_{>20}$, dødt ved og totale kulstoflagre 16 år efter hugst. Vi har ligeledes konstateret, at SOC-lagrene også var påvirket af hugstintensitet, men i kombination med øvrige variabler. Dermed har vi bekræftet, at hugst, især hugstintensitet, styrer skovenes kulstoflagre. Derudover har vi også bekræftet den specifikke hypotese, at desto højere hugstintensitet, jo mindre total kulstoflager i skovene.

**Hovedspørgsmål: I hvilket omfang påvirker hugst hver kulstoflager og de samlede kulstoflagre i Dipterocarp-skove på Borneo?**

Vores undersøgelse har vist, at tre kulstoflagre ($AGC_{>20}$, $BGC_{>20}$ og dødt ved) blev direkte påvirket af hugst. Da disse kulstoflagre repræsenterer ca. 70% af al kulstof i vores undersøgelsesområde var de samlede kulstoflagre også påvirket af hugst. Endvidere blev SOC-lagre (100 cm dybde) også påvirket af hugst, men i kombination med de andre variabler, dvs. lerindhold, kulstofmængden i førne og hældning.

Vores resultater tyder på, at ved at fokusere på de mest betydningsfulde kulstoflagre, som generelt er rapporteret til at udgøre >80% af det samlede kulstof lager i tropiske skove, fandt vi at de samlede kulstoflagre var signifikant påvirket af hugstintensitet 16 år efter skovning og bekræfter dermed vores hypotese. Det mest interessante resultat er omdannelsen fra levende biomasse ($AGC_{>20}$ og $BGC_{>20}$) til dødt materiale. Mens døde neotropiske træer er blevet rapporteret til at miste 90% af deres biomasse inden for to årtier, var dødt ved lagrene ca. 3 gange højere i intensivt huggede områder (>19% fjernelse af indledende biomasse) end i områder med lavt hugstintensitet. Et stort hugstspild (fx glemte stammer) og store tilfældigt dræbte træer kan forklare denne forskel 16 år efter hugst. Endvidere ligger en anden forklaring i forøget dødelighed blandt resterende træer efter hugst i intensivt huggede stande. Dødeligheden efter skovning viste sig at toppe kort efter skovningen, og forblev høj efter et årti sammenlignet med skove uden hugst. Dette afspejler de langsigtede virkninger af skovning på skovøkosystemer og en tenderende sænket resiliens med stigende hugstintensitet. En væsentlig problemstilling er at vurdere hvor længe disse negative konsekvenser varer, og hvordan de påvirker økosystemets funktion. Vi fandt ud af, at flere kulstofpuljer kan forudsiges relativt godt alene gennem hugstintensitet, udtrykt som en procentdel af den indledende biomasse, der er tabt. Desværre er oplysninger om hugstintensitet normalt utilgængelige. Med den hurtige udvikling af remote-sensing teknikker, som muliggør registrering af selv små forandringer i levende biomasse, kan udvikles modeller der bruger hugstintensitet som forklarende variabel, som et effektivt surrogat til at estimere de samlede kulstoflagre og andre kulstof-puljer (især for $AGC_{>20}$ og $BGC_{>20}$, marginal $R^2$ >60%). Vores resultater bekræfter også forudgående fund om vigtigheden af dødt ved puljen i degraderede skove og behovet for at redegøre for andre kulstofpuljer, når der skal foretages præcise beregninger af kulstoflagre og -strømme i tropiske skove påvirket af mennesker.

Med hensyn til SOC-lagrene viste vores resultater, at SOC-lagrene i det 30 cm øvre lag og de samlede SOC-lagre (0-100 cm) blev forklaret og negativt påvirket af hugstintensiteten. Imidlertid var hugstintensiteten ikke den eneste variabel, der forklarede variationerne for disse to akkumulerede lag. I det 30 cm øvre lag var variabiliteten bedst forklaret af hugstintensitet, lerindhold og hældning. I 0-100 cm laget blev variationerne i SOC-lager bedst forklaret ved hugstintensitet, lerindhold, C-lagret i førnen og hældning.

## Konklusion

De samlede kulstoflagre i udrevne skove eller skove med lav hugstintensitet var i gennemsnit højere (351 Mg C $ha^{-1}$) end dem der blev fundet i områder med mellem (316 Mg C $ha^{-1}$) eller høje hugstintensiteter (256 Mg C $ha^{-1}$). Samtidig var andelen af dødt ved 5 gange højere i stærkt huggede områder, op til 13,5% af den samlede kulstofpulje. Mens kulstofpuljen responderede anderledes på skovning og nogle få vigtige miljøvariabler, blev hugstintensiteten alene fundet som den vigtigste faktor, der forklarer variabiliteten i $AGC_{>20}$, $BGC_{>20}$, dødt ved og totale kulstoflagre. Levende træer forbliver den vigtigste kulstofpulje 16 år efter hugst, efterfulgt af en betydelig mængde kulstof i dødt ved og SOC. Da hugstintensitet påvirker kulstofpuljerne i vores forsøgsområde, vil det få konsekvenser for kulstoflageret i fremtiden. I betragtning af at 32% af 114,1 millioner hektar permanent skovområder er udpeget som permanent produktionsskov i Indonesien, vil en indsnævring af de estimerede kulstoflagre i huggede skove være et vigtigt skridt for det nationale system til afrapportering af kulstofregnskab (National Carbon Accounting System). Vores resultater kastede således lys over den langsigtede effekt af skovning på kulstofkredsløbet i produktionsskove i Indonesien, og bekræftede behovet for at begrænse hugstintensiteten til en tærskel på 20% af den oprindelige biomasse, for at begrænse langsigtet ophobning af dødt ved efter skovning, hvilket sandsynligvis er en konsekvens af høj dødelighed efter hugst.

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